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Abstract of Dissertation Presented to the Graduate School of the University of Florida in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy

APPLICATIONS OF THE ELECTRONIC CONE PENETRATION TEST FOR THE GEOTECHNICAL SITE INVESTIGATION OF FLORIDA SOILS

(246 pp.)

By

KENNETH JAMES KNOX
Captain, USAF

1989

The purpose of this research project was to evaluate techniques to improve the application of in situ penetration testing to Florida soils, with emphasis on the electronic cone penetrometer test (ECPT). Statistical Analysis was used to describe the spatial variability of soil properties, to classify Florida soils with the ECPT, and to correlate the ECPT with the standard penetration test (SPT).

The spatial variability study was carried out to evaluate methods of interpolation between test soundings. The techniques studied included three deterministic approaches, three distance-weighting methods, a random field model, and regression analysis.

The ECPT classification study used discriminant analysis of cone data on soils that had been identified from the SPT test. The ECPT was able to group soil accurately into one of seven categories (organics, clay, silt, clayey sand, silty sand, sand, weathered rock) approximately 40% of the time.

In the SPT-ECPT correlation study, average q_c/N ratios for Florida

soils were much higher than expected, possibly due to cementation or liquefaction. Regression analysis of the data suggested that the nature of the SPT-ECPT relationship is more a function of the magnitude of the cone resistance, and less of the actual soil type.

Key References:

Penetration Testing 1988, Vol. 2, J. deRuiter (Ed.), A.A. Balkema, Rotterdam, 1988.

Use of In Situ Tests in Geotechnical Engineering, Geotechnical Special Publication No. 6, Samuel P. Clemence (Ed.), ASCE, NY, 1986.

Robertson, P.K. et al., "SPT-CPT Correlations," Journal of Geotechnical Engineering, ASCE, NY, Nov. 1983.

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By

KENNETH JAMES KNOX

A DISSERTATION PRESENTED TO THE GRADUATE SCHOOL
OF THE UNIVERSITY OF FLORIDA IN PARTIAL FULFILLMENT
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DOCTOR OF PHILOSOPHY

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1989

DEDICATED WITH ALL MY LOVE TO MY WIFE, PAT,

AND TO MY WONDERFUL CHILDREN, BRIAN AND KELLY,

FOR THEIR DEVOTED LOVE, PATIENCE, AND SUPPORT.

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So many people had a direct and significant impact on my studies and research at the University of Florida that I am reluctant to attempt to write the acknowledgments section for fear of omitting a key contributor. Nevertheless, fear must never be allowed to impede progress and worthwhile endeavors; therefore, please forgive my less-than-perfect memory if I fail to acknowledge someone, and know that I am deeply indebted to and appreciative of everyone I have been associated with these past three years.

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superb teaching style in my own return to teaching. Special thanks are extended to Dr. Joseph N. Wilson of the Department of Computer and Information Sciences for being an old friend of the family and for serving as my external committee member.

I have purposely left Dr. Michael C. McVay to the end of my committee members. Dr. McVay was singularly instrumental in, and the driving force behind every phase of my research. He insured that I had the resources I needed to accomplish the work. Dr. McVay constantly challenged and encouraged me throughout the project, and the final product is a direct result of his interest not only in the research, but also in me. My deepest thanks are extended to Dr. McVay for his support. I pray that some of Dr. McVay's thirst for knowledge will rub off on me when I depart the University of Florida.

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I would like to express my sincerest appreciation to the United States Air Force for making this doctorate possible. In particular, I would like to express my thanks to the U.S. Air Force Academy and Colonel (Dr.) David O. Swint, Professor and Head of the Academy Department of Civil Engineering. They helped make my dream come true.

Lastly, but not least by a long shot, I would like to thank my wonderful family for their endless devotion and support. Completion of my doctorate would not have been possible without my wife Pat's undying love, nurturing, prodding, scolding, supporting, and caring for me. My little buddy, Brian, and my lovely little girl, Kelly, were bottomless sources of joy to me when I most needed a lift. This doctorate truly belongs to all of them.

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APPLICATIONS OF THE ELECTRONIC CONE PENETRATION TEST FOR THE GEOTECHNICAL SITE INVESTIGATION OF FLORIDA SOILS

By

KENNETH JAMES KNOX

August 1989

Chairman: Dr. Frank C. Townsend
Major Department: Civil Engineering

The purpose of this research project was to evaluate techniques to improve the application of in situ penetration testing to Florida soils, with emphasis on the electronic cone penetrometer test (ECPT). Topics addressed included describing the spatial variability of soil properties, classifying Florida soils with the ECPT, and correlating the ECPT with the standard penetration test (SPT). A collateral purpose was to create an in situ test data base consisting of 97 ECPT soundings and 79 SPT tests. This data base was subsequently evaluated using statistical analysis.

The spatial variability study was carried out to evaluate methods of interpolation between test soundings. The techniques studied included three deterministic approaches (the mean, median, and a 10% trimmed average), three distance-weighting methods (two based on reciprocal distances, and linear interpolation), a random field model (a hybrid distance-weighting/regression model), and regression analysis. While none of the approaches stood out as consistently superior

predictors, the deterministic approaches were generally inferior to the other, more sophisticated methods. The distance-weighting methods and the random field model performed comparably, but were sensitive to individual test soundings. The regression models predicted slightly better on the average, and with more stability.

The ECPT classification study used parametric and nonparametric discriminant analysis of cone data on soils that had been identified from the SPT test. The ECPT was able to group soil accurately into one of seven categories (organics, clay, silt, clayey sand, silty sand, sand, weathered rock) approximately 40% of the time. This percentage increased to 70% when the three sand categories were combined, reflecting the SPT drillers' difficulties in discriminating silty soils.

In the SPT-ECPT correlation study, average q_c/N ratios for Florida soils were much higher than expected, possibly due to cementation or liquefaction. Regression analysis of the data suggested that the nature of the SPT-ECPT relationship is more a function of the magnitude of the tip resistance, and less of the actual soil type.

CHAPTER 1
INTRODUCTION

Seeking solutions to the problems of transferring superstructure loads to the supporting ground is typically the responsibility of the geotechnical engineer. Solutions to this interface problem are many and diverse depending on the nature and magnitude of the loads involved; the geology of the site; and the economic, environmental, and political climate of the project. The economic impact of foundations can be considerable. Vanikar reports that nearly 20% of approximately 2.6 billion dollars worth of highway construction by the Federal Highway Administration and the state transportation departments in fiscal year 1984 was spent on foundations (62).

In all but the simplest of projects, a site investigation of the underground conditions is necessary. This investigation, which usually costs between 0.5 and 1% of the total construction costs (8), should provide the geotechnical engineer with enough information to characterize the site geology, select the type of foundation required, determine the load capacity of the soil and/or rock, and estimate the settlements of the superstructure. There is a large number of in situ tests and equipment available to help obtain this information, including the standard penetration test (SPT), the cone penetration test (CPT), the Marchetti dilatometer test (DMT), the Menard and the self-boring pressuremeters, the vane shear test, and others.

The Florida Department of Transportation (FDOT) uses the SPT and the CPT in the design of axially loaded pile foundations (53). In the standard penetration test, a standard split-barrel sampler is attached to drill rods and inserted into a predrilled borehole. The sampler is then driven 45.7 cm (18 in) using a 63.6 kg (140 lb) hammer and a 76.2 cm (30 in) drop height. The split-barrel sampler is then withdrawn and opened, providing a physical sample of the soil. The SPT "N-value" equals the number of blows for the final 30.5 cm (12 in) of penetration. These N-values have been correlated to many soil parameters despite considerable criticism as to their reproducibility. The SPT is standardized by the American Society for Testing and Materials (ASTM) Standard Method D 1586 (2).

In the cone penetration test using an electronic cone penetrometer (designated ECPT), a cylindrical rod with a conical point is pushed into the ground at a constant, slow rate, and the force on the point is measured by an internal strain gauge. A second strain gauge measures the force caused by friction on a free-floating friction sleeve. The ECPT provides an accurate description of the subsurface stratification and, from simple correlations, an estimate of the soil type. Also, many soil properties have been correlated with the ECPT measurements. The principal disadvantages of the cone penetration test are the lack of a soil sample from the test, and the penetrometer's limited ability to penetrate stiff soil layers. The CPT is standardized by the ASTM Standard Method D 3441 (2).

The design procedures for pile foundations depend on an accurate representation of the soil at the location of the pile, both in terms of the measured or estimated soil properties, and the type of soil.

Uncertainty in the input parameters determined by the SPT or CPT will naturally result in uncertainty in the calculated pile load capacity. The need exists to describe and quantify the uncertainty in the input parameters, as well as to use procedures which minimize the uncertainty associated with a site investigation program.

Purpose of Research

The purpose of this research project is to evaluate methods to improve the use of in situ penetration tests for the geotechnical site investigation of soils indigenous to Florida. In support of the University of Florida's driven pile study, the project concentrates on construction sites employing driven pile foundations. The primary in situ device to be evaluated is the electronic cone penetrometer, which is thought to model a pile foundation. This emphasis is the result of the ECPT's faster speed, better reproducibility, and lower cost relative to the standard penetration test.

Specifically, methods to describe the spatial variability of soil properties will be evaluated with the purpose of determining the method which can best interpolate test measurements between soundings. The ability of the ECPT to classify Florida soil types will also be evaluated, and procedures recommended to improve current Florida practice. Finally, correlations between the SPT N-values and the ECPT cone resistance and friction resistance will be determined. These correlations will be valuable in situations when the cone penetrometer test cannot be used due to stiff soil layers or difficult access.

A collateral purpose for this research project is to develop a data base of pile load tests and in situ tests for Florida. Such a data base will prove extremely valuable to future geotechnical research on Florida soils.

Research Methodology

The initial phase of the research project involved setting up a data base of pile load tests and in situ tests performed throughout Florida. A letter soliciting data and site access was sent to all of the FDOT district geotechnical engineers, and to many private geotechnical consulting firms. As a result of the letter and follow-up telephone contacts, a significant amount of information was collected. These data included site plans, pile load tests, pile driving records, standard penetration tests, mechanical and electronic cone penetration tests, wave equation analyses (CAPWAPC), and Marchetti dilatometer data. Numerous trips to sites with driven pile load tests were also made in order to collect electronic cone penetration test (ECPT) data using the University of Florida cone penetration testing vehicle and equipment.

In order to handle this large data base and to run statistical analyses on the data, the SAS™ System was used (SAS is a registered trademark of the SAS Institute Inc., of Cary, North Carolina). The SAS System is computer software that provides data retrieval and management, reporting and graphics capabilities, and an extensive array of elementary and advanced statistical analysis procedures (47,48,49,51). As the data were collected, they were encoded and stored on a computer for future analysis. To date the encoded data base includes pile load tests (PLTs), electronic cone penetration tests (ECPTs), standard penetration tests (SPTs), and some mechanical cone penetration tests (MCPTs). Additional data are on file at the University of Florida, and can be encoded as required by future research. Chapter 2 describes the data base used by this research project.

Once the in situ test data were available to the SAS System, the individual data sets were combined into larger sets (depending on the nature of the study) for statistical analysis. The spatial variability studies were accomplished using the SAS data manipulation and reporting capabilities, coupled with regression analysis and exploratory data analysis. The soil classification study employed the SAS discriminant analysis procedures. The SPT/ECPT correlation study used exploratory data analysis and regression analysis.

CHAPTER 2
PROJECT DATA BASE

Introduction

The data base was created in support of the University of Florida Department of Civil Engineering's Deep Foundations Project, sponsored by the Florida Department of Transportion. The specific focus of this phase of the project is the design of axially-loaded driven piles and pile groups. As a result, data were solicited on construction sites having driven pile load test data. Letters and telephone calls were made to all of the FDOT district geotechnical engineers, and to many geotechnical consultants in Florida. When suitable sites were identified, all available geotechnical data were obtained.

In order to obtain electronic cone penetration test (ECPT) data coinciding with the pile load tests (PLTs), site visits were made to perform ECPTs if the data were not otherwise available (which was generally the case). ECPT soundings were made near the pile load tests, and also adjacent to standard penetration test borings that were near the PLTs. These latter soundings were designed to support the classification study of the ECPT.

This chapter describes the nature and extent of the entire project data base. Subsequent chapters describe the parts of the data base used for the individual analyses. This chapter also describes the procedures and equipment used for the ECPTs performed by the University of Florida, including a discussion of some of the problems and limitations associated with the electronic cone penetration test.

Extent of Data Base

Figure 2-1 is a map of the State of Florida, showing the thirteen cities where test data were collected. Table 2-1 summarizes the number of tests at each site that have been entered into the computer data base. Note that multiple pile load tests at a site usually indicate multiple tests on the same pile (either the pile was redriven, or a tension test was performed). Note also that additional data from many of the sites are available, but have not yet been encoded and stored in the computer. These tests are generally either not pertinent to this study (the Marchetti dilatometer tests for instance), or are not close to pile load tests of interest. The majority of these data is comprised of SPT and MCPT data.

A more extensive description of the Table 2-1 data base is located in Appendix A, which is an index of the data base. This index is organized by location (generally of the pile load test). Each individual test is identified by a prefix to identify the type of test, a number to identify the location, and a suffix to identify individual tests. The prefixes are shown below the test abbreviations in Table 2-1. For instance, C001B is an electronic cone penetration test (the prefix C) at Pier 3 of the Apalachicola River bridge (the number 001), and is the second test at that location (the suffix B). The index includes information on general soil conditions, a description of the pile used in the pile load test, the file name used by the source of the data, and any important additional comments. The data base itself is contained in Knox (25).

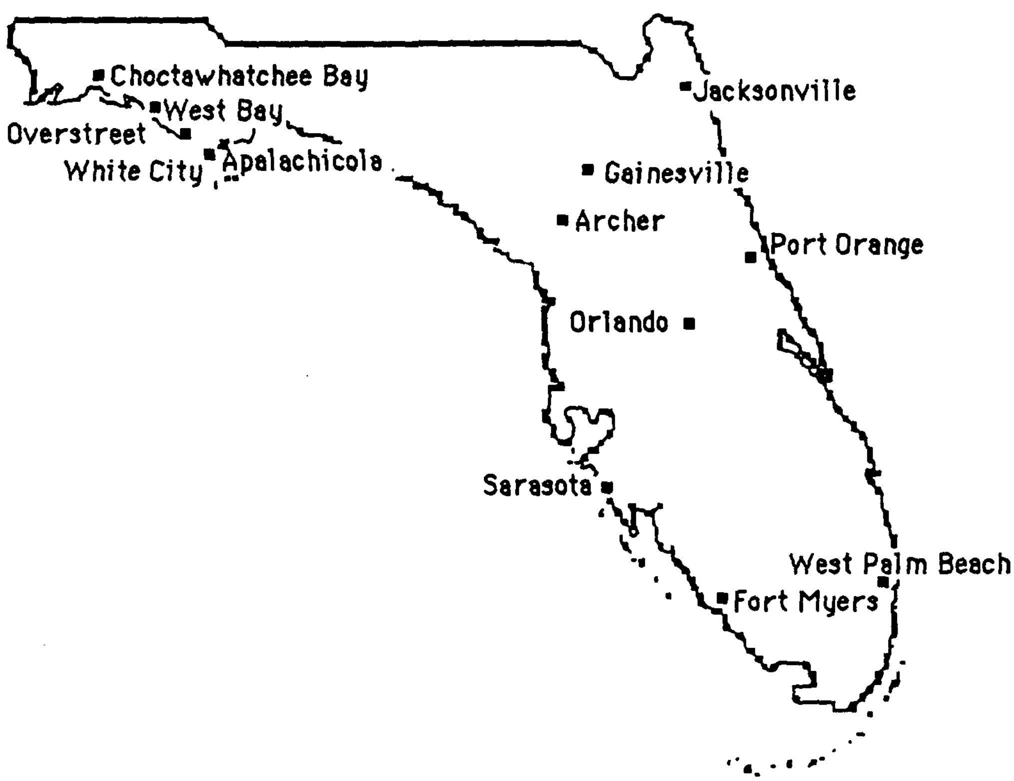


Figure 2-1. Cities Represented in Pile Data Base

Table 2-1. Data Base Summary

LOCATION NUMBER	SITE	PLTs (P)	ECPTs (C)	SPTs (S)	MCPTs (M)
001	Apalachicola River Bridge--Pier 3	1	2	20	4
002	Apalachicola River Bridge--Bent 16	1	2	0	2
003	Apalachicola Bay Bridge--Bent 22	1	2	0	4
004	Overstreet Bridge--Pier 11	1	4	2	0
005	Overstreet Bridge--Pier 16	1	4	4	0
006	Sarasota Garage--SP7	2	4	4	0
007	Sarasota Garage--SP5	2	4	5	0
008	Sarasota Condo	2	2	5	0
009	Sarasota Landfill	0	3	3	0
010	Fort Myers--Concrete Pile	2	8	2	0
011	Fort Myers--Steel Pile	1	0	0	0
012	Fort Myers Airport	0	2	2	0
013	Port Orange--Bent 19	1	2	0	2
014	Port Orange--Bent 2	1	1	1	2
015	West Palm I-95--Pier B-4	1	3	1	0
016	West Palm I-95--Pier B-6	0	3	1	0
017	West Palm I-95--Pier B-9	1	2	1	0
018	West Palm I-95--Pier C-2	1	0	1	2
019	Choctawhatchee Bay--Pier 1	1	13	3	1
020	Choctawhatchee Bay--Pier 4	1	2	1	2
021	Choctawhatchee Bay--Bent 26	1	4	1	3
022	White City	0	3	3	3
023	Orlando Arena	2	4	5	0
024	Orlando Hotel South	1	2	2	0
025	Orlando Hotel North	1	1	1	0
026	Orlando Hotel Northeast	1	1	1	0
027	Jacksonville Terminal B-20	2	3	1	0
028	Jacksonville Terminal B-21	2	2	1	0
029	Archer Landfill	0	7	2	0
030	West Bay Bridge	0	6	6	0
031	Lake Wauberg	0	1	0	0
	TOTALS	31	97	79	25

Site Descriptions

Apalachicola River and Bay Bridges (Sites 001 - 003)

The Apalachicola River and Bay bridges are replacement structures for older bridges on U.S. Highway 98 in Apalachicola. Both are FDOT projects. The Apalachicola River bridge is a 1153 m (3783 ft) structure running generally east and west, with a turn to the north on its western end. The Apalachicola Bay bridge is a 4321 m (14175 ft) structure traversing the bay east and west.

The available test data for these sites include test pile driving records, CAPWAPC analyses, pile load tests (PLTs), standard penetration tests (SPTs), Marchetti dilatometer tests (DMTs), mechanical cone penetration tests (MCPTs), and University of Florida electronic cone penetration tests (ECPTs). The soils are predominantly clays, sands, and clay/sand mixtures. Figure 2-2 locates the Apalachicola River bridge SPTs used in the spatial variability studies. Figures 2-3 through 2-5 locate the available in situ soil test data available near the pile load tests in the data base.

Overstreet Bridge (Sites 004 - 005)

The Overstreet bridge is a 962 m (3157 ft) structure over the Intracoastal Waterway on State Road 386, near the town of Overstreet, Florida. This FDOT project is a replacement for an old floating pivot bridge. The available test data include test pile driving records, PLTs, SPTs, MCPTs, and ECPTs. The soils are mostly sand, with some clayey sand and clay. Figures 2-6 and 2-7 locate the available in situ soil test data near the pile load tests in the data base.

Sarasota Garage and Condo (Sites 006 - 008)

The Sarasota parking garage (Sites 006 and 007) and the Sarasota condo site (Site 008) are supported by a pile foundation designed by Ardaman & Associates of Sarasota. The available test data include test pile driving records, PLTs, SPTs, and ECPTs. The soils at the parking

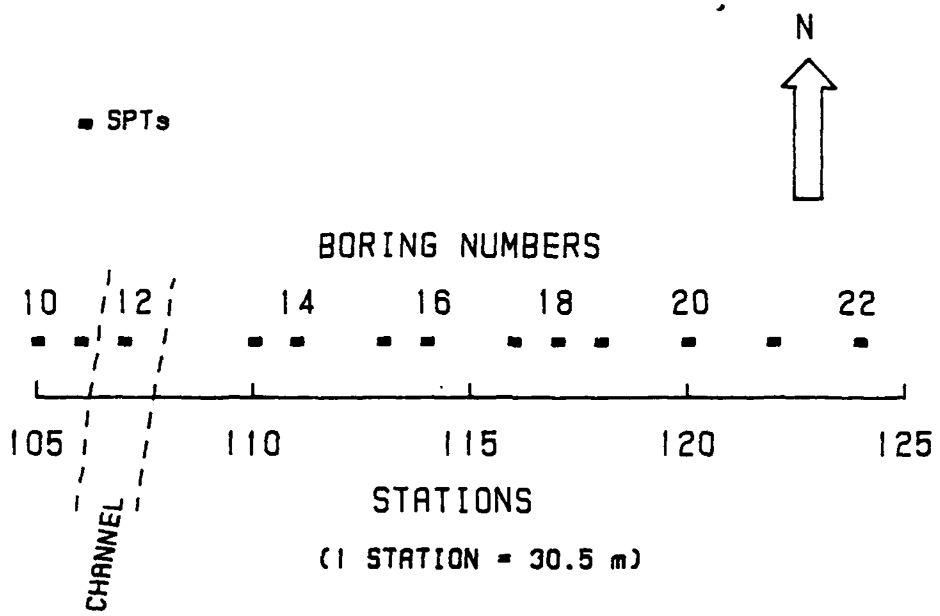


Figure 2-2. Apalachicola River Bridge SPTs Used for Spatial Variability Studies

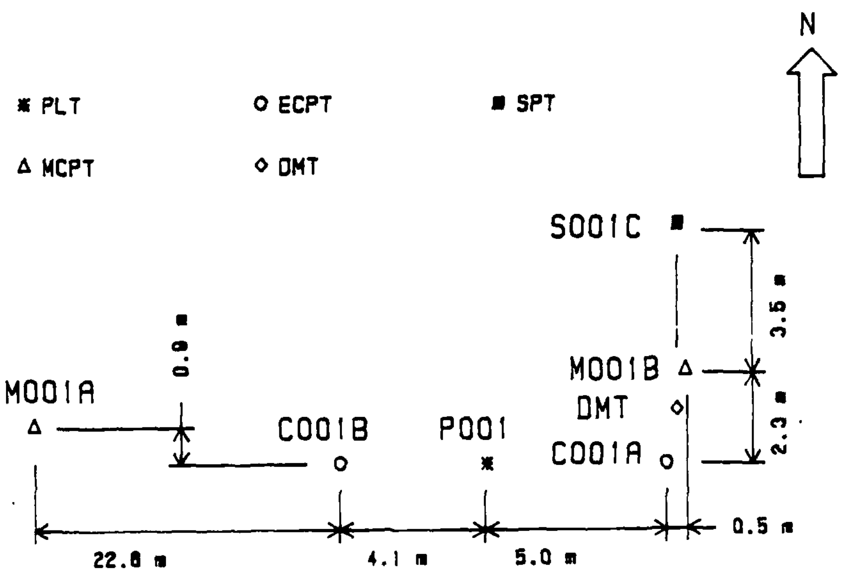


Figure 2-3. Apalachicola River Bridge Pier 3 Tests

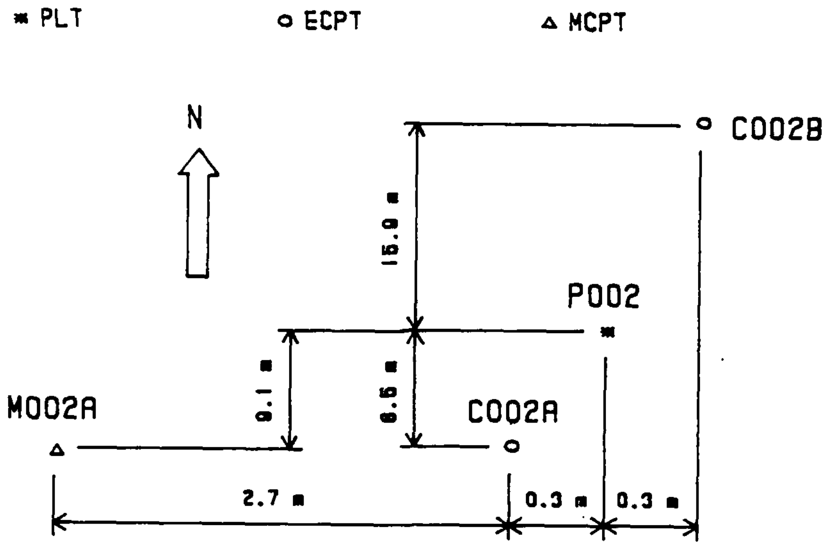


Figure 2-4. Apalachicola River Bridge Flat Slab Bent 16 Tests

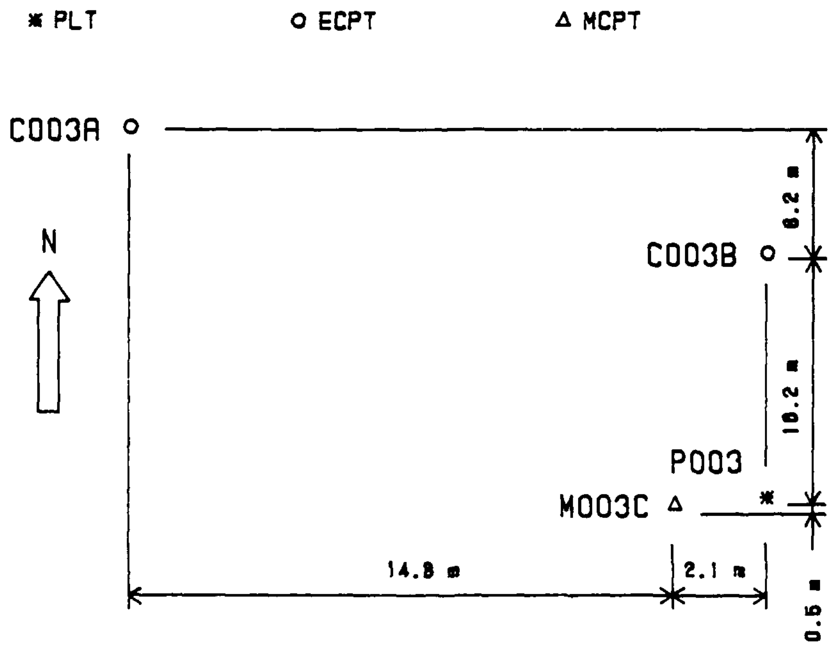


Figure 2-5. Apalachicola Bay Bridge Flat Slab Bent 22 Tests

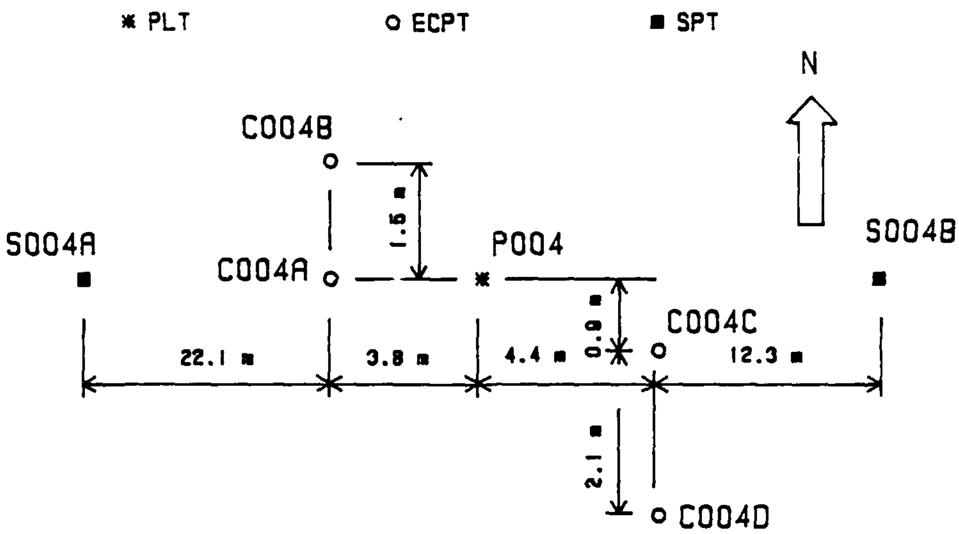


Figure 2-6. Overstreet Bridge Pier 11 Tests

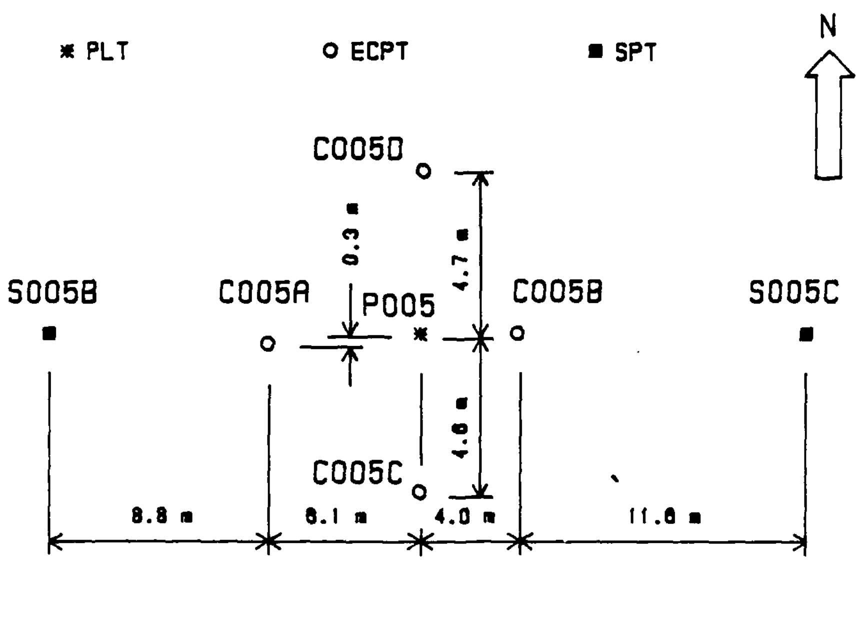


Figure 2-7. Overstreet Bridge Pier 16 Tests

garage are mostly sand overlying limestone rock at approximately 7.6 m depth (25 ft). The condo site is predominantly fine sand and clayey sand overlying limestone at approximately 5.5 m depth (18 ft). Figures 2-8 and 2-9 locate the available in situ soil test data near the pile load tests in the data base.

Sarasota Landfill (Site 009)

The Sarasota (Manatee County) landfill is located north of Sarasota. No pile load tests are available for this site, but Ardaman & Associates of Sarasota provided some SPT data, which were supplemented with UF ECPT soundings. ECPT sounding C009A is 0.76 m (2.5 ft) from SPT sounding S009A; 122 m (400 ft) southeast, C009B is 0.76 m from S009B; 61 m (200 ft) further southeast, C009C is 0.5 m (1.5 ft) from S009C. The soils at the landfill are mostly clayey fine sand, with some clay and sandy clay.

Fort Myers Interchange (Sites 010 - 011)

The Fort Myers site is a highway interchange project designed by Greiner Engineering of Tampa, with Law Engineering Testing Company of Naples serving as the geotechnical consultant. Available test data include test pile driving logs, pile load tests, SPTs, and ECPTs. Several of the ECPTs were rate-controlled tests (0.5 to 2.0 cm/s), although the nonstandard tests were not used in this project. The soil is sand and sand/clay mixture overlying cemented clayey sand at a depth of 31 m (102 ft). Figure 2-10 locates the test data in the data base.

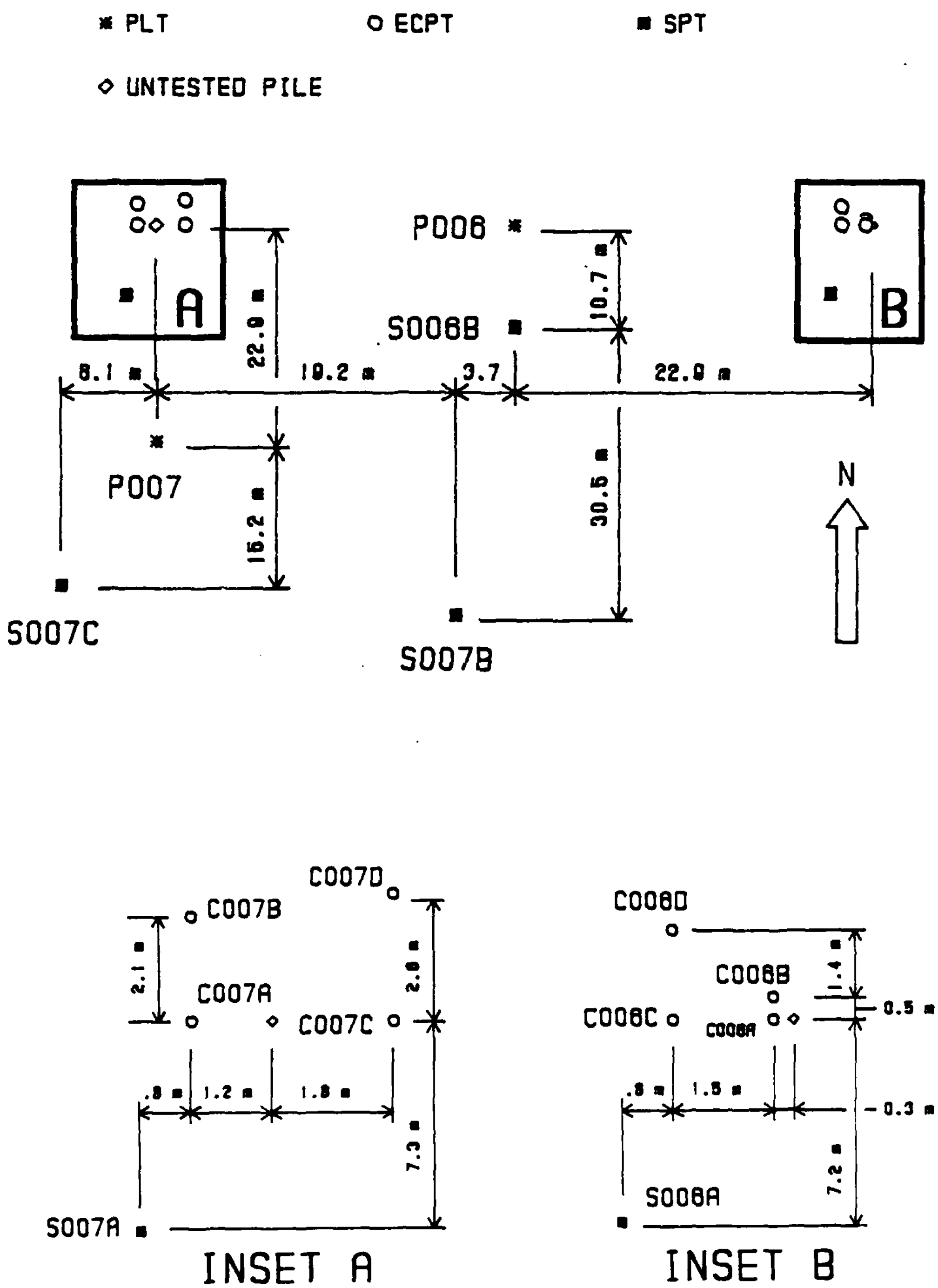


Figure 2-8. Sarasota Garage Tests

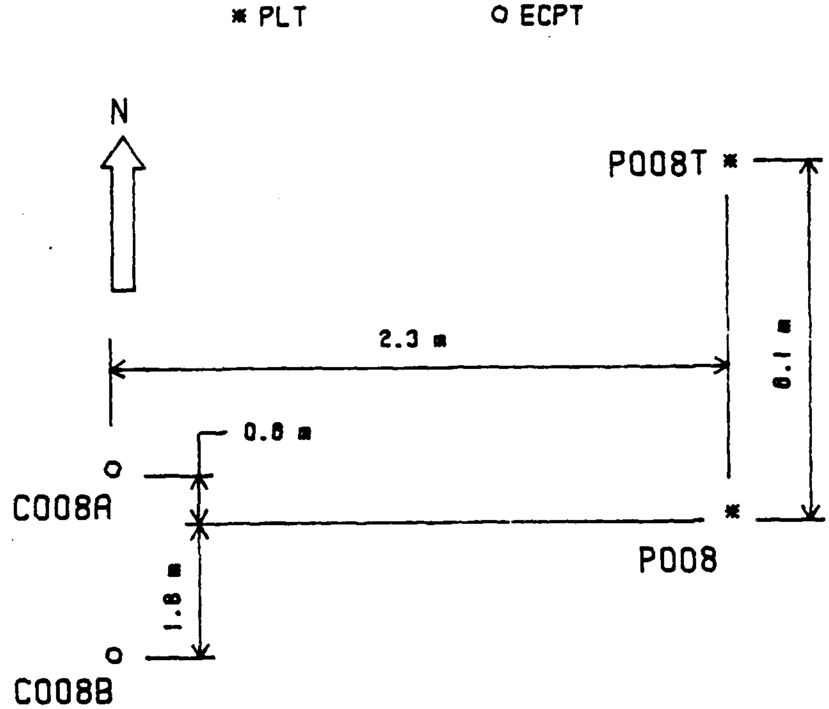


Figure 2-9. Sarasota Condo Tests

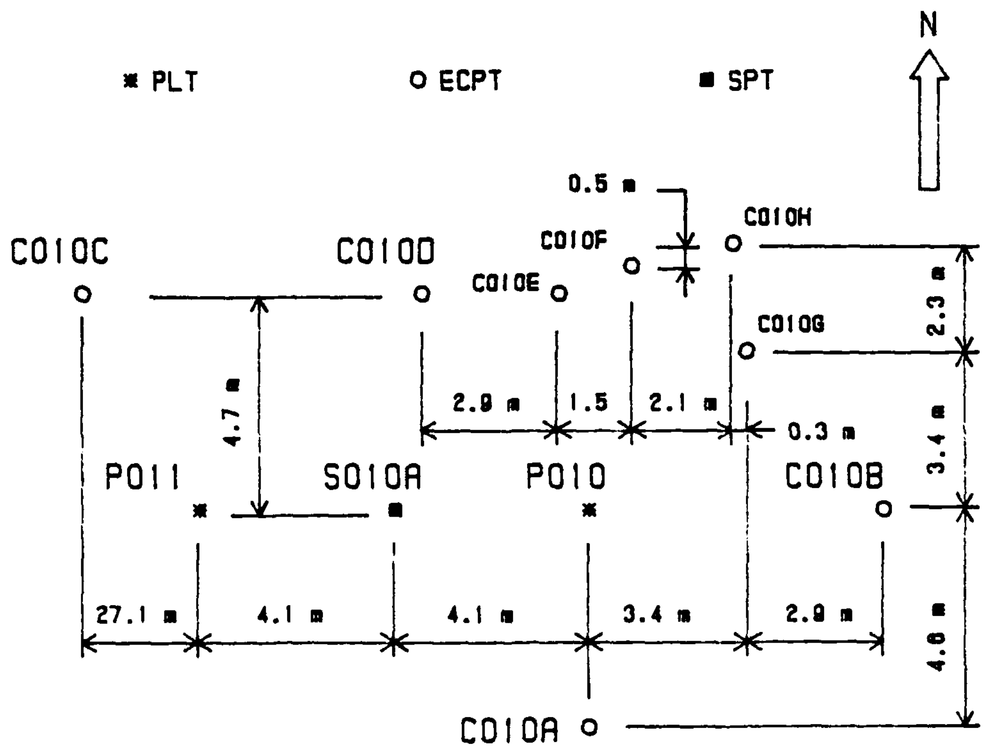


Figure 2-10. Fort Myers Interchange Tests

Fort Myers Airport (Site 012)

The Fort Myers airport site is an interchange project, with Law Engineering Testing Company of Naples serving as the geotechnical consultant. Available test data include SPTs, ECPTs, and some laboratory test data. The soil is comprised of sand and sand/silt/clay mixtures, interbedded with weak to competent limestone layers. Two SPT sites were used, separated by approximately 23 m (75 ft). ECPT sounding C012A is 1.37 m (4.5 ft) from SPT S012A, and C012B is 1.52 m (5 ft) from S012B.

Port Orange (Sites 013 - 014)

The Port Orange site is an FDOT bridge on State Road A1A over the Halifax River. The foundation for this bridge uses driven piles on the approaches and drilled shafts under the main spans. The data base includes PLTs, SPTs, MCPTs, ECPTs (both UF and FDOT), CAPWAPC analyses, and laboratory analyses. The soil is mostly shelly sand and sandy silt, with a 4.5 to 6m (15 to 20 ft) thick clay layer overlying limestone at approximately 26 m (85 ft) in depth. Figures 2-11 and 2-12 identify the test data near the pile load tests in the data base.

West Palm I-95 (Sites 015 - 018)

This recently-completed project consisted of ramps and overpasses for Interstate 95 in Palm Beach County. The data base include test pile driving records, PLTs, SPTs, ECPTs (for the P.G.A. Boulevard ramp, Sites 015 - 017), and MCPTs (for the Military Trail overpass, Site 018). The soil is fine sand with a small amount of clayey fine sand. Figures 2-13 through 2-16 locate the test data near the pile load tests.

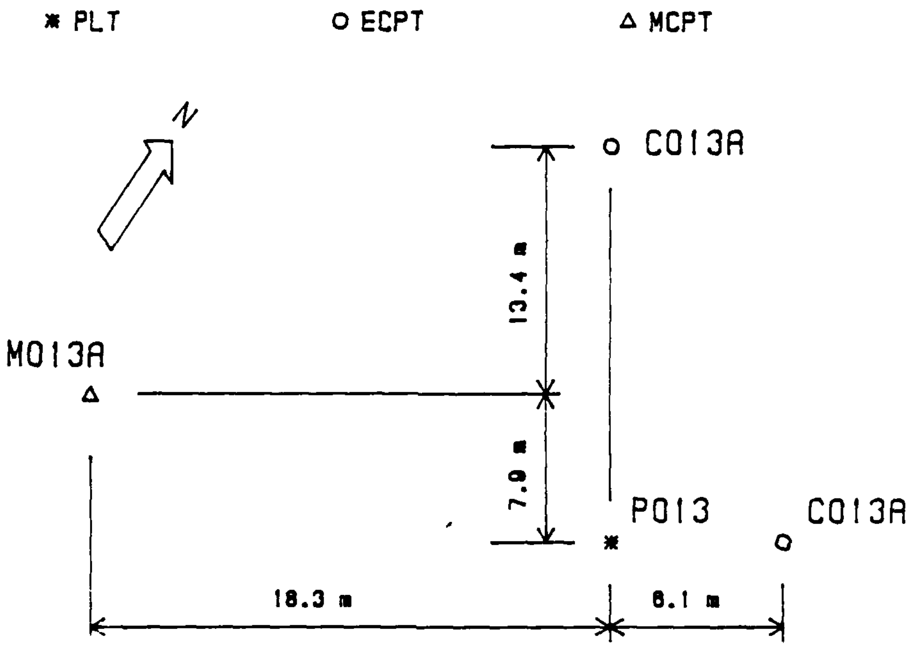


Figure 2-11. Port Orange Bent 19 Tests

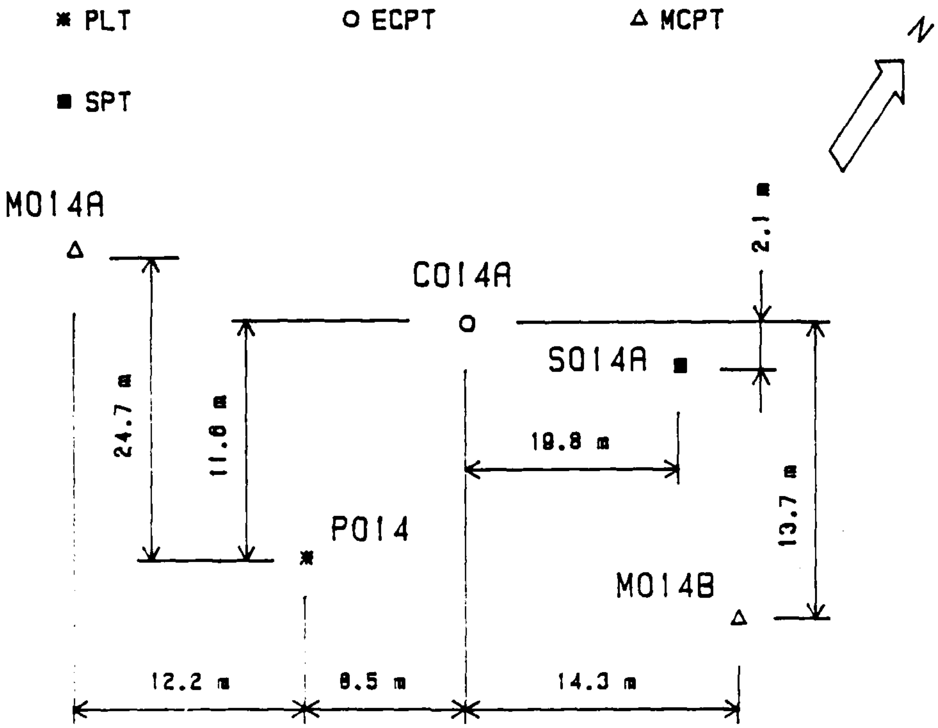


Figure 2-12. Port Orange Bent 2 Tests

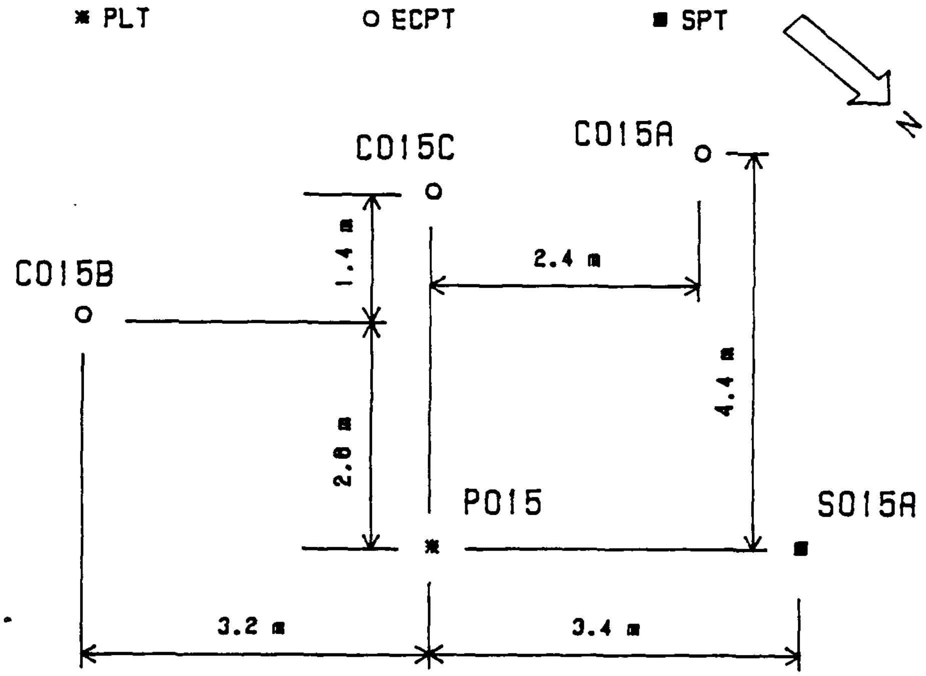


Figure 2-13. West Palm I-95 Pier B-4 Tests

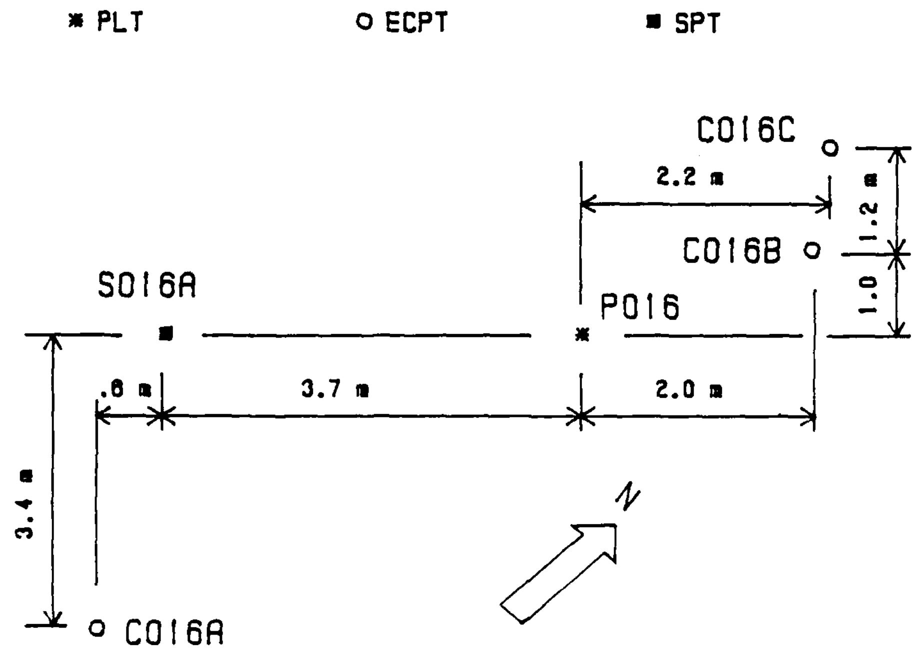


Figure 2-14. West Palm I-95 Pier B-6 Tests

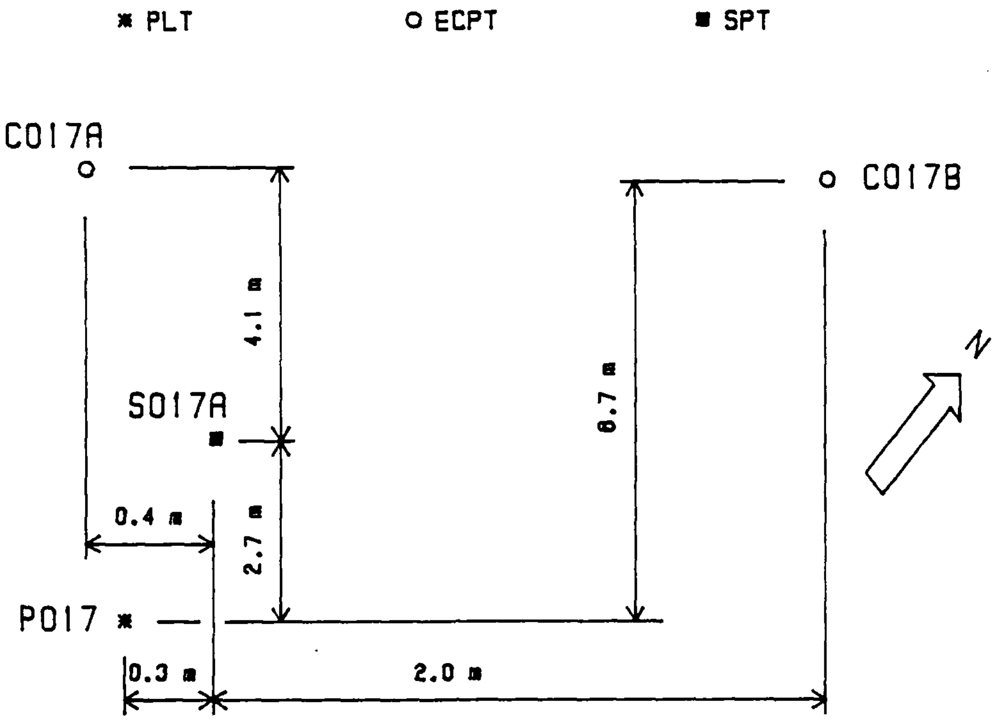


Figure 2-15. West Palm I-95 Pier B-9 Tests

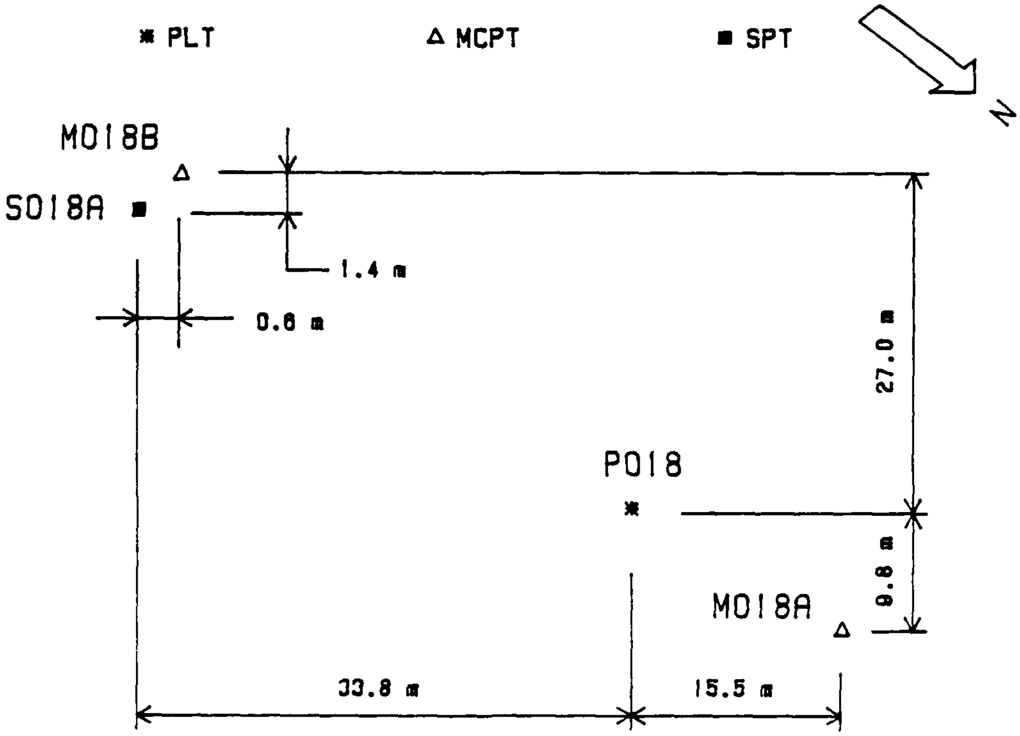


Figure 2-16. West Palm I-95 Pier C-2 Tests

Choctawhatchee Bay (Sites 019 - 021)

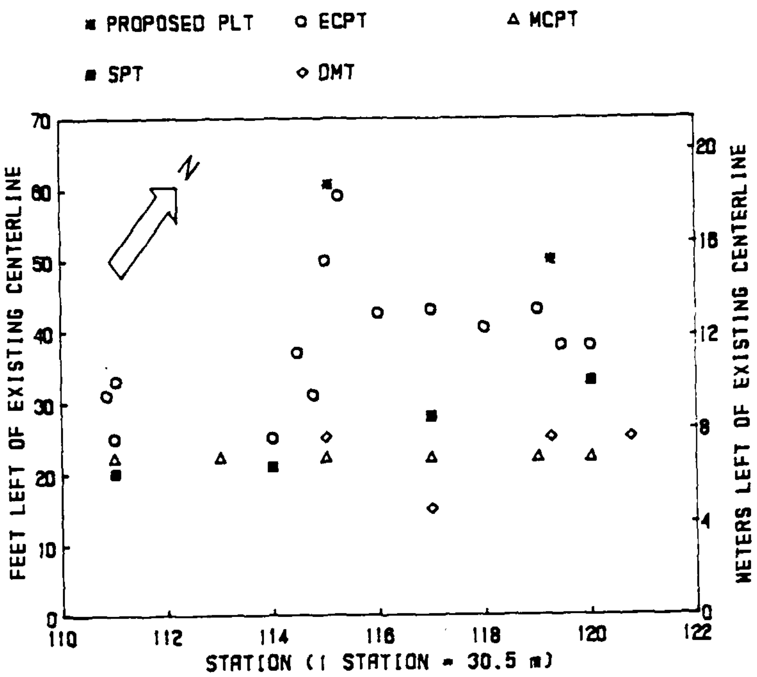
The Choctawhatchee Bay bridge is a replacement structure for an older bridge on State Road 83 (U.S. 331). The bridge portion of this FDOT project is approximately 2296 m (7534 ft) long, running north and south. Available test data include PLTs, SPTs, MCPTs, ECPTs (both FDOT and UF), DMTs (available from FDOT), and laboratory test data performed by both the FDOT and the University of Florida. The soils are predominantly sand overlying some clays and clayey sand on the southern approach to the bridge, with the clays increasing as you proceed north. Many of the ECPTs on the south side of the bridge were used in the spatial variability studies. Figures 2-17 and 2-18 identify the in situ test data in the data base.

White City (Site 022)

The White City bridge is a replacement structure over the Intracoastal Waterway on State Road 71. The bridge portion of this FDOT project is approximately 549 m (1800 ft) long, running north and south. Available test data include SPTs, MCPTs, ECPTs, and laboratory data. Pile load test data should be available in the near future. The soils are mostly sand, with some clayey sand. Figures 2-19 and 2-20 locate the available test data near the UF ECPTs.

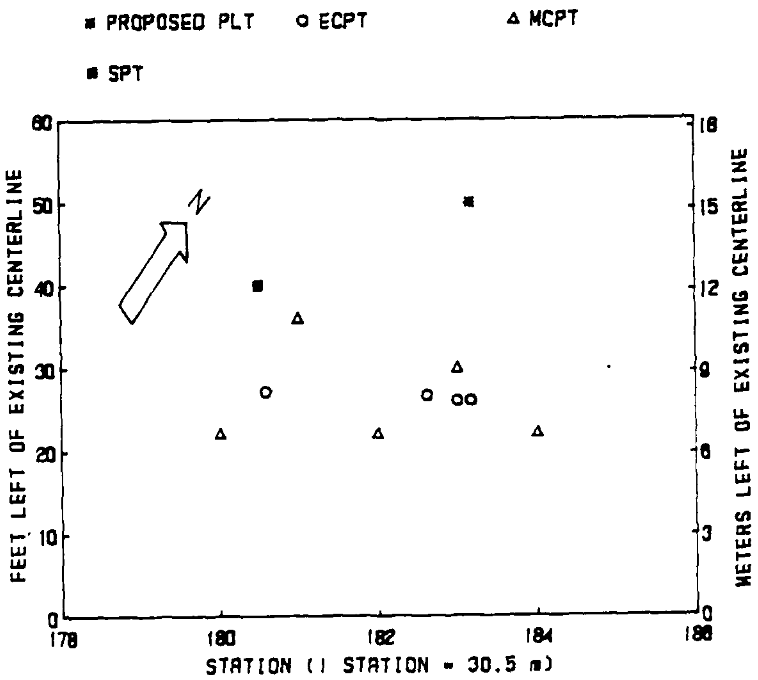
Orlando Arena (Site 023)

The Orlando Arena is a 15,000 plus-seat structure constructed by the City of Orlando. Jammal & Associates of Orlando performed the geotechnical investigation, and kindly provided all of the test data used in this project. Available data include test pile driving records,



Note: See Appendix A for test identification.

Figure 2-17. Choctawhatchee Bay South Tests



Note: See Appendix A for test identification.

Figure 2-18. Choctawhatchee Bay North Tests

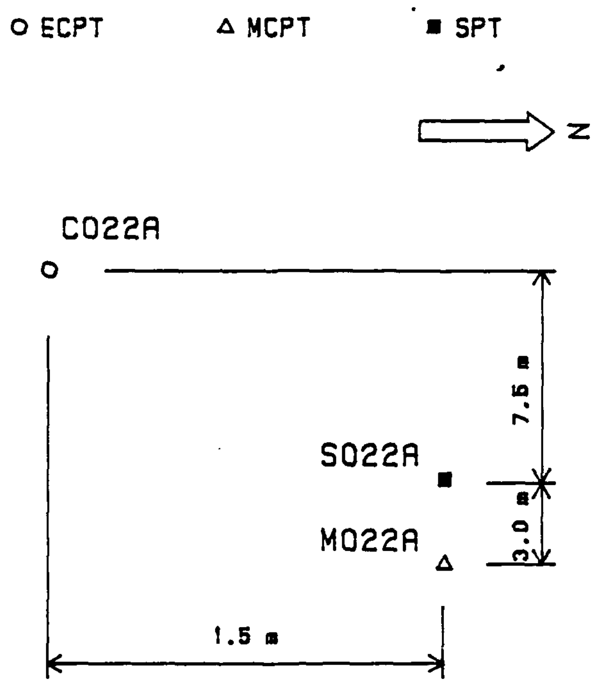


Figure 2-19. White City South Tests

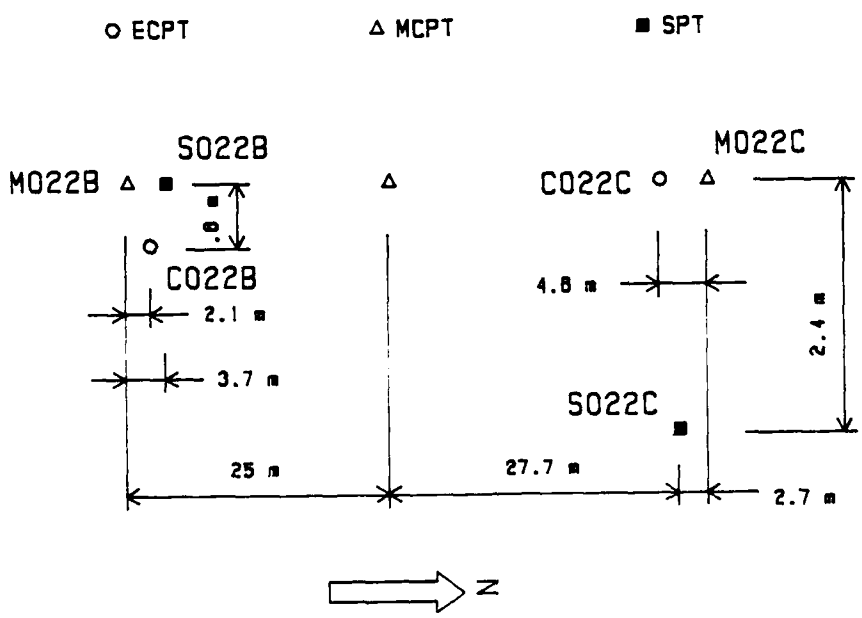


Figure 2-20. White City North Tests

PLTs, auger borings, SPTs, ECPTs, and laboratory test data. The site is mainly sand overlying mixed clay and sand at depths of 12 to 18 m (40 to 60 ft), with consolidated clays and silts being encountered at depths of approximately 33.5 m (110 ft). Figure 2-21 locates the in situ test data used in this project.

Orlando Hotel (Sites 024 - 026)

The Orlando Hotel is a proposed high-rise structure in downtown Orlando. Jammal & Associates of Orlando performed the geotechnical investigation, and provided all of the test data used in this project. Available data include test pile driving records, PLTs, SPTs, ECPTs, and laboratory test data. The site is comprised of a surficial sand fill overlying fine sand with some silt and clay to a depth of 13 to 16 m (43 to 53 ft). Below this depth are mixed sands, silts, and clays characteristic of the Hawthorn Formation. Figure 2-22 identifies the test data used in this project.

Jacksonville Terminal (Sites 027 - 028)

This project was the addition of a coal conveyer system to the St. John's River Coal Terminal on Blount Island. The geotechnical consultant for the project was Law Engineering of Jacksonville. The available data include test pile driving records, PLTs, CAPWAPC analyses, SPTs, and ECPTs. The exact location of the PLTs and SPTs could only be estimated at the time of the electronic cone penetration tests, but all tests are believed to be very near one another. The three ECPTs were spaced in a line at 1.5 m (5 ft) increments for Site 027, whereas the two ECPTs at Site 028 were 1.8 m (6 ft) apart. The soils are predominantly fine sand and silty sand.

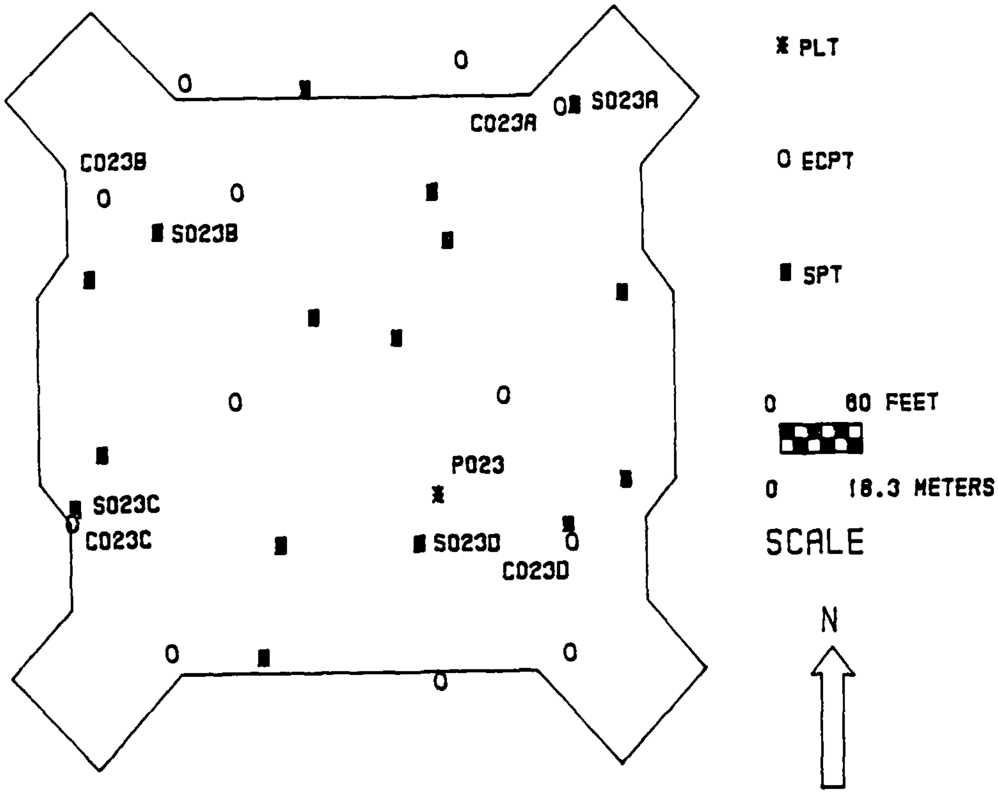


Figure 2-21. Orlando Arena Tests

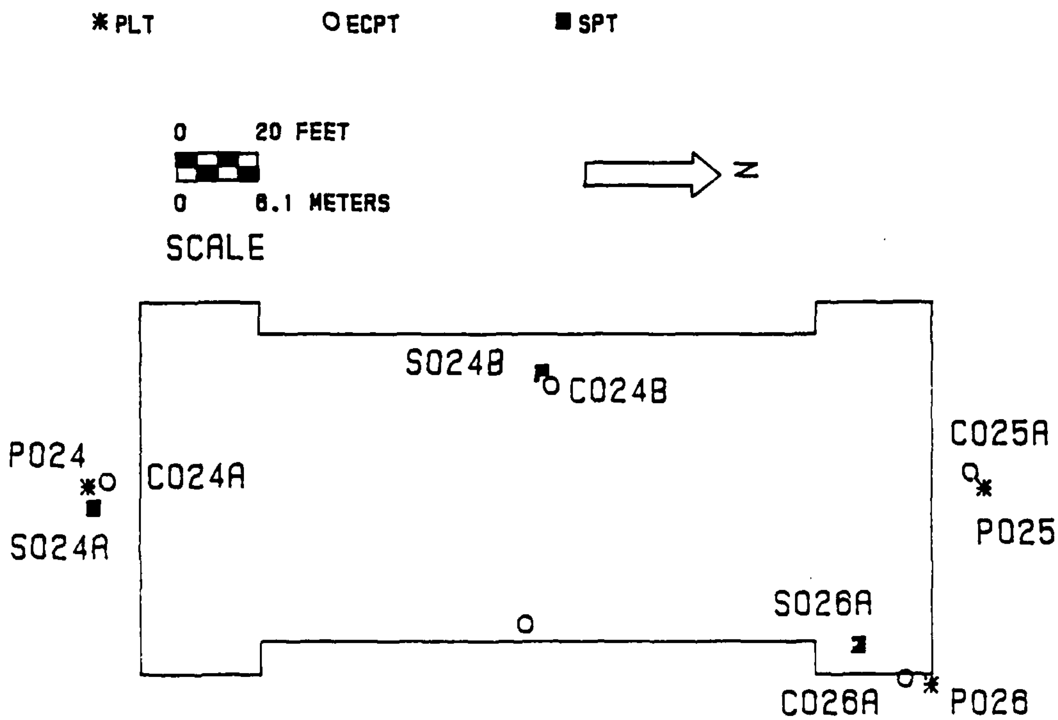


Figure 2-22. Orlando Hotel Tests

Archer Landfill (Site 029)

This Alachua County landfill site is covered by ancient sand dunes which overlie limestone at approximately 15 m (50 ft) of depth. The source for the data at this site is a Master's thesis by Basnett (7). The site is remarkably uniform, and was used for the spatial variability studies. Available soils data include SPTs, ECPTs, UF laboratory data, and DMTs. Figure 2-23 identifies the test sites pertinent to this study.

West Bay (Site 030)

The West Bay site is an FDOT bridge on State Road 79. All of the in situ test data for this site was provided by the FDOT, and includes approximately 29 SPTs and 14 ECPTs. Laboratory data from both FDOT and UF are also available. The soils are mostly fine sand with some silts and clays. Some of the silty sand is slightly cemented. Figure 2-24 locates the test data used in this project.

Lake Wauberg (Site 031)

The Lake Wauberg site is located on University of Florida property south of Gainesville. The ECPT sounding for this site came from Basnett (7). This sounding was correlated with the results of UF laboratory analyses on recovered samples of highly plastic clays and elastic silts, the results of which are included in the classification studies.

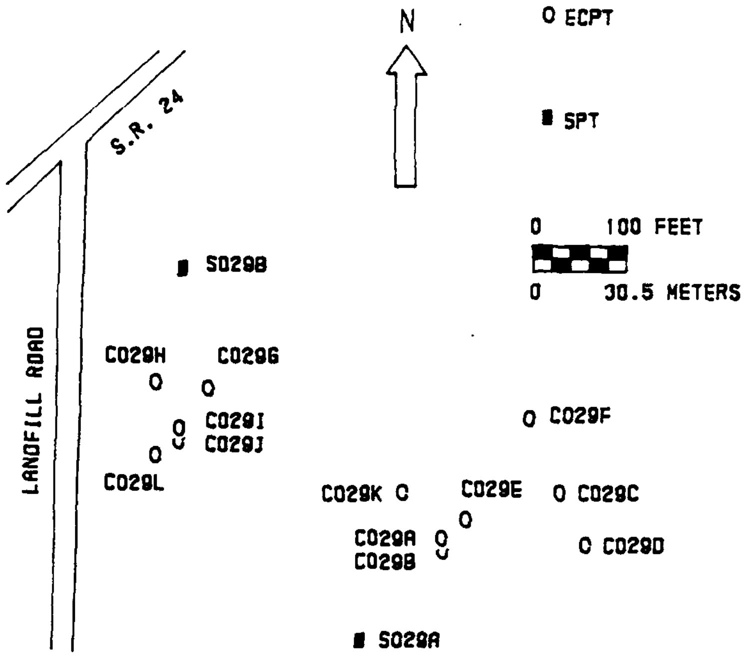


Figure 2-23. Archer Landfill Tests

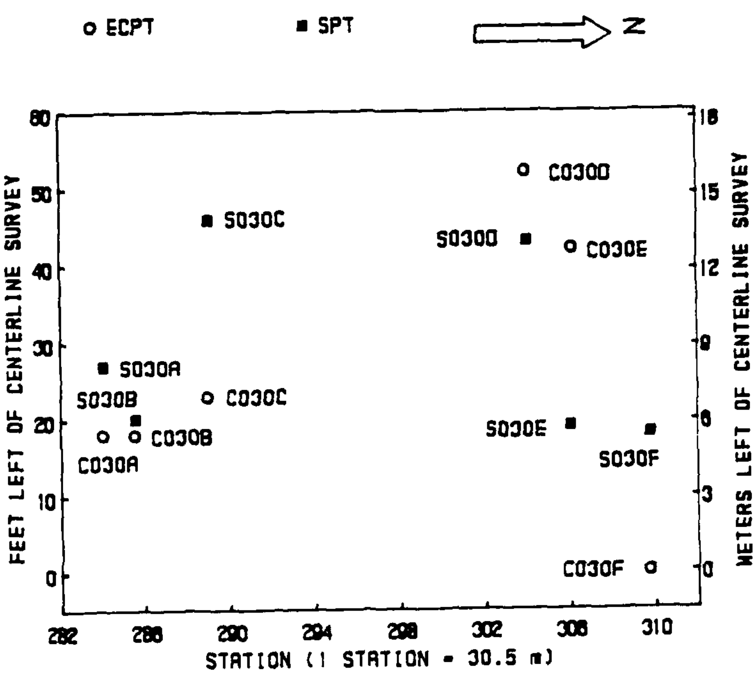


Figure 2-24. West Bay Tests

Collection of ECPT Data

Equipment

All of the electronic cone penetration test data was obtained using University of Florida equipment, with the exception of two of the Port Orange soundings (source: FDOT), the Orlando data (source: private consultant), and the West Bay data (source: FDOT). Three electronic friction-cone penetrometers were used in the research, rated at 5-tons (metric), 10-tons, and 15-tons respectively. All three are subtraction-type friction-cone penetrometer tips marketed by Hogentogler and Company, Inc. of Columbia, Maryland. Figure 2-25 is a schematic drawing of a subtraction-type penetrometer tip.

The American Society of Testing and Materials (ASTM) has standardized the cone penetrometer and the cone penetration test in ASTM Standard D 3441 (2). The standard penetrometer tip has a 60° cone with a base diameter of 35.7 mm (1.406 in.), resulting in a projected area of 10 cm^2 (1.55 $in.^2$). The standard friction sleeve has the same outside diameter as the cone, and a surface area of 150 cm^2 (23.2 $in.^2$). The UF 5-ton and 10-ton penetrometer tips conform to this standard, whereas the 15-ton penetrometer's 60° cone has a base diameter of 43.7 mm (1.72 in.) for a projected area of 15 cm^2 (2.33 $in.^2$). The friction sleeve, however, has the standard 150 cm^2 surface area.

Two primary measurements are made by the friction-cone penetrometer. The cone resistance, q_c, is defined as the vertical force applied to the cone divided by its projected area. The friction resistance, f_s, is the vertical force applied to the friction sleeve divided by its surface area. The friction resistance is comprised of both frictional and adhesive forces.

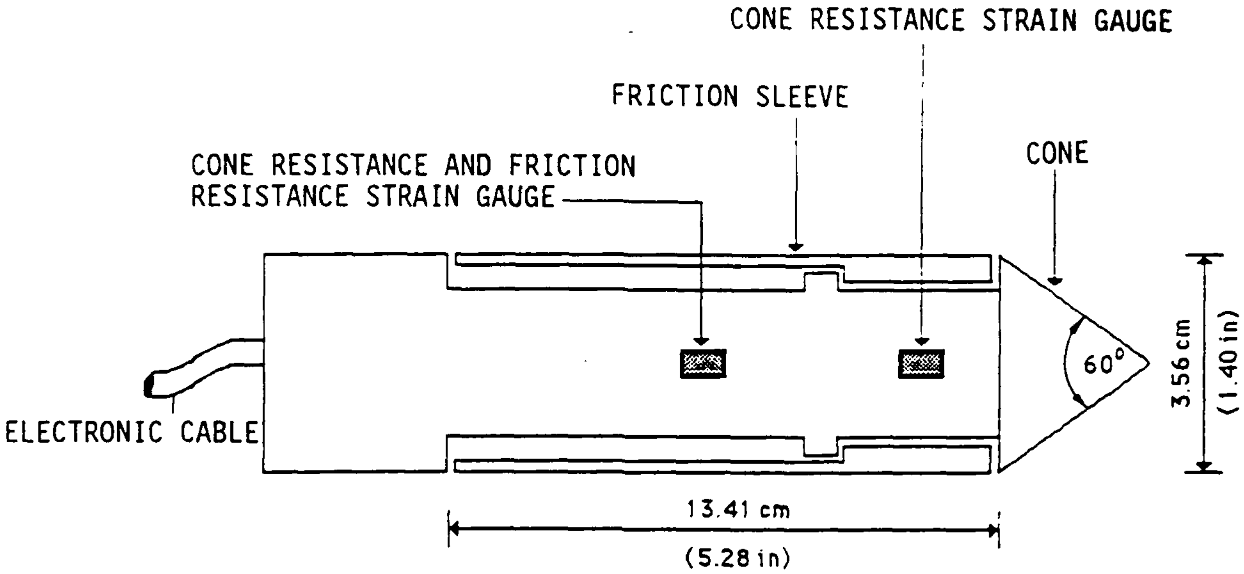


Figure 2-25. Subtraction-Type Electronic Friction-Cone Penetrometer Tip

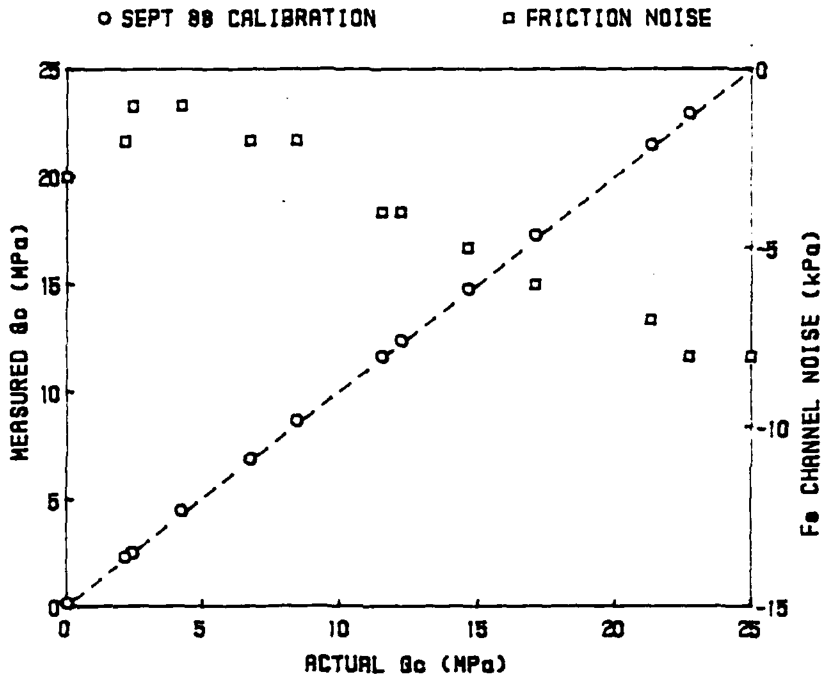
Figure 2-26. The UF Penetration Testing Vehicle

One of the advantages of electronic penetrometers is that other electrical measuring devices can be incorporated into the tip housing to provide additional and specialized information about the soil being penetrated. The UF penetrometer tips incorporate two additional devices, an inclinometer and a pore pressure transducer.

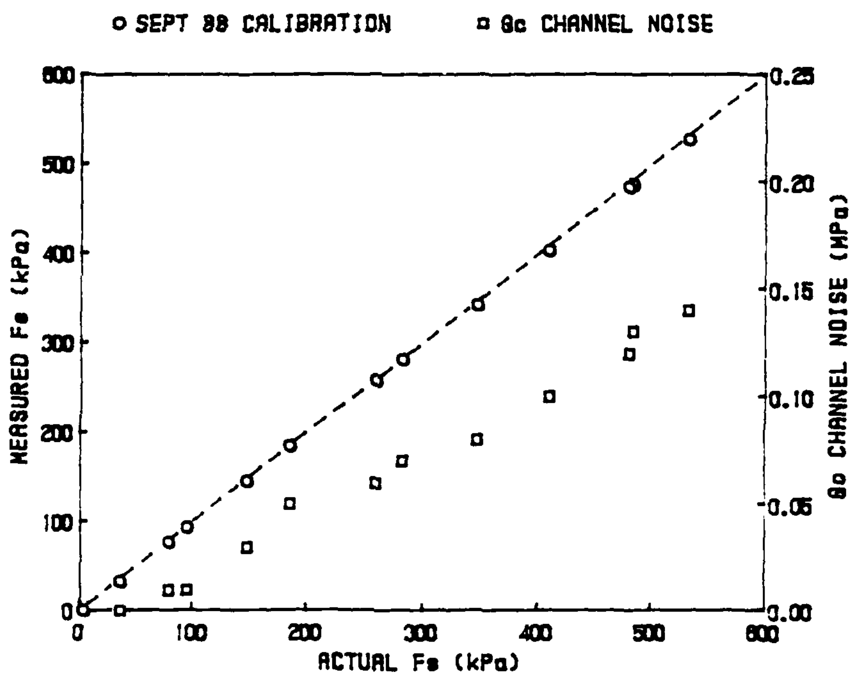
The precision optical inclinometer is primarily a safety device. It measures the angular deviation of the penetrometer tip from vertical during penetration, warning the operator of possible drifting during penetration of stiff layers.

Dynamic pore pressures are measured using a small pressure transducer mounted within the penetrometer tip. The plastic porous filter element is located immediately behind the cone. The filter element is carefully boiled in a water/glycerin mixture to completely saturate it. Saturation of the tip is maintained prior to use by a rubber sheath around the filter element.

Insertion of the penetrometer tip and collection of the data were accomplished using the University of Florida's cone penetrometer testing truck. This vehicle includes a 20-metric-ton hydraulic ram assembly, four independently-controlled jacks for leveling, and a computer-operated data acquisition system. The data acquisition system is comprised of a microprocessor with a 128k magnetic bubble memory, a keyboard, a printer, and a graphics plotter. The system permits real time monitoring of the ECPT test, built-in overload factors for safety, and permanent recording of the data. The system is described in detail in Davidson and Bloomquist (11). Figure 2-26 shows the UF penetrometer testing vehicle.

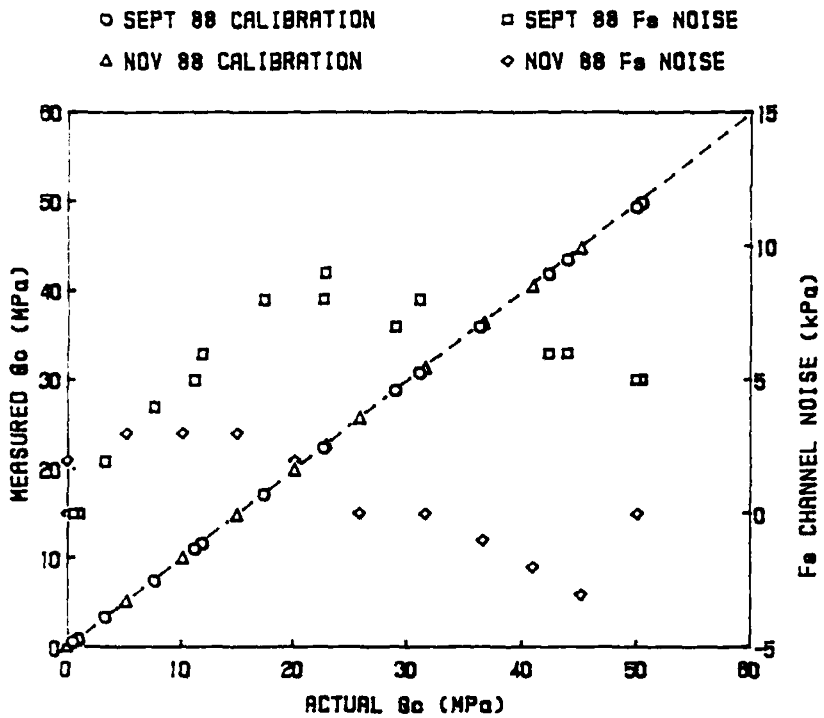


(A) Qc Calibration

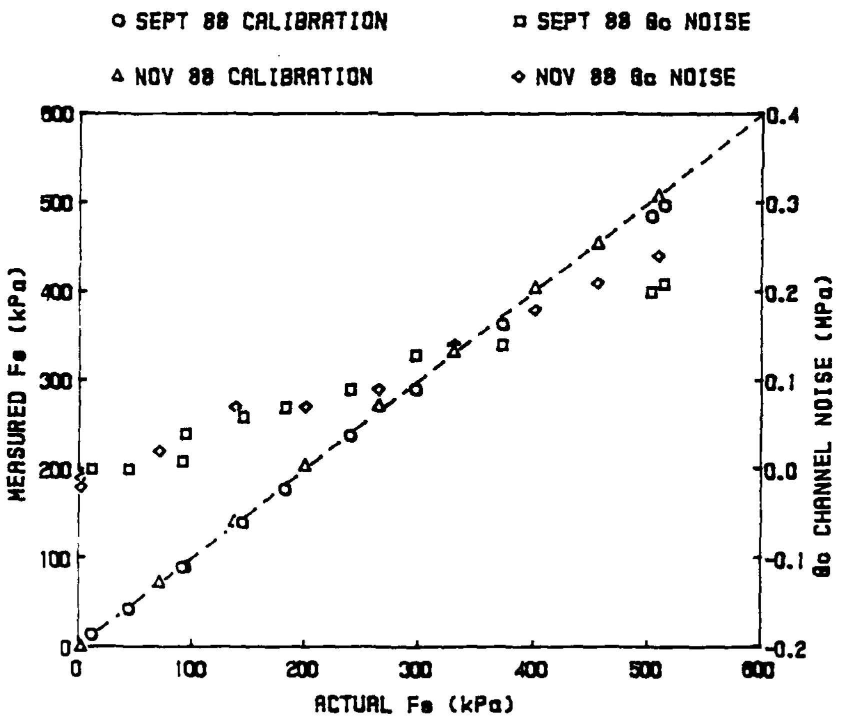


(B) Fs Calibration

Figure 2-27. Calibration for 5-Ton Friction-Cone Penetrometer

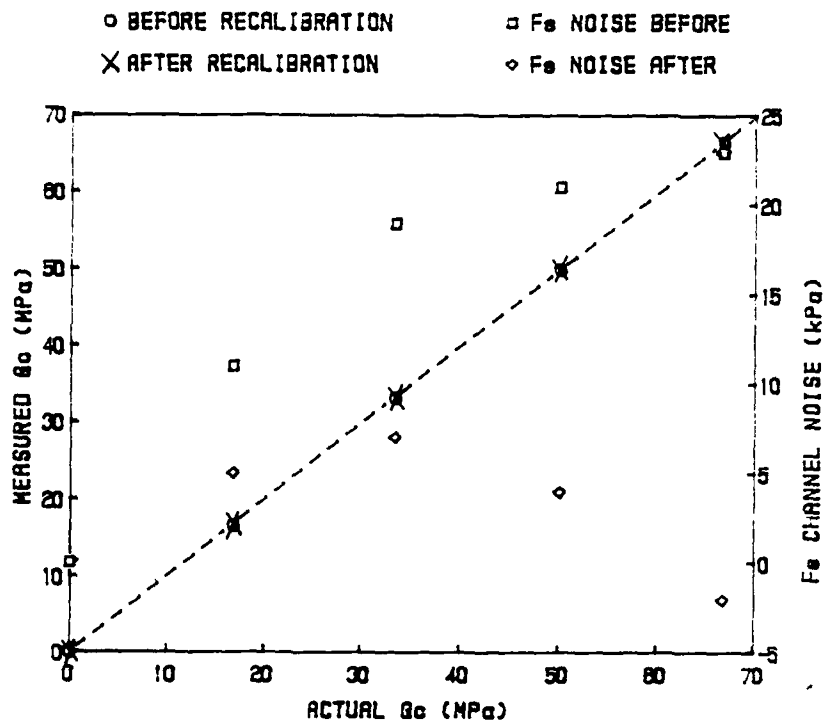


(A) Qc Calibration

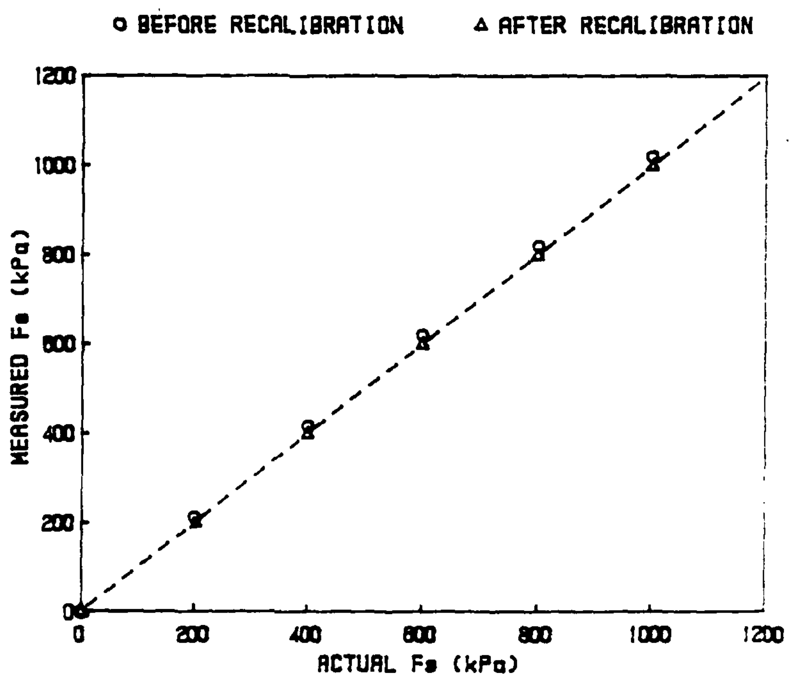


(B) Fs Calibration

Figure 2-28. Calibration for 10-Ton Friction-Cone Penetrometer



(A) Qc Calibration



(B) Fs Calibration

Figure 2-29. Calibration for 15-Ton Friction-Cone Penetrometer

friction noise readings were poor prior to repair, however, reading as much as 23 kPa (0.240 tsf) too high. Following repair, the maximum friction noise was 7 kPa (0.073 tsf). The friction channel read as much as 14 to 20 kPa too high for the higher friction resistance measurements prior to the repair. All friction measurements made by the 15-ton cone penetrometer prior to August 1988 are suspect as a result of the calibration.

Baseline drift and negative values. The worst problem encountered in the project was negative friction resistance measurements and friction baseline drifts, primarily in the 15-ton penetrometer tip. Physically, negative friction resistance measurements are impossible since the friction sleeve is free-floating, recording a "true" friction value only when the sleeve bears on a shoulder of the central core, as shown in Figure 2-25. Therefore, some type of measurement error must be present.

Several sources of the problems are possible (13,18-23,41,50). Regarding the baseline drift problems, the manufacturer defines an "allowable" drift of 1.0 to 1.5% of the full-scale reading. The 1.5% limit equates to a drift of 1.5 MPa (15.7 tsf) for the q_c channel, 15 kPa (0.157 tsf) for the f_s channel, and 0.4 bar (5.8 psi) for the pore pressure channel. Only the friction channel even approached this limit, exceeding it on several occasions. While temperature effects on the strain gauges may account for a small portion of the problem, the literature suggests the single biggest cause of baseline drift is soil and water ingress during a sounding. Therefore reasonably rigorous attention to cleanliness (under field conditions) was exercised throughout the project. Despite this care, the 15 kPa limit on friction baseline drift was approached fairly regularly, slightly exceeded occasionally, and on a few occasions was exceeded by a large amount. All baseline drifts slightly exceeding 15 kPa were flagged in the data base index (Appendix A), and all clearly unacceptable baselines were discarded.

The negative friction readings (predominantly on the 15-ton penetrometer tip) can be partially explained by the unstable baselines. If the baseline value drifts positively 10 kPa, then a friction reading that would have read 5 kPa under the original baseline now reads -5 kPa. The manufacturer also notes that transient voltage surges may temporarily affect measurement readings, resulting in negative values (22). A third potential source for error is due to the design of the subtraction-type electronic friction-cone penetrometer tip (41). The cone load cell measures the cone resistance, and the friction load cell measures the resistance on both the cone and the friction sleeve. The friction resistance is then determined by subtracting the cone load cell measurement from the friction load cell measurement. While this particular design is rugged and robust, the calculation of a small number (f_s) by subtracting two large numbers is not good measurement practice.

Weak soils. Accurate measurements in weak soils are extremely difficult to obtain. A potential source of error is due to unequal end areas on the cone and the friction sleeve (41,43,50). Below the water table, pore pressures bear on the horizontal surfaces at the joints in the penetrometer tip. For the UF 10-ton tip, these unequal end areas would increase q_c by 0.034 MPa/bar pressure (0.025 tsf/psi), and increase f_s by 1.0 kPa/bar (0.00072 tsf/psi). While the change in q_c is virtually negligible over the normal range of pore pressures of -2 to 6 bars (-29 to 87 psi), the change in friction could be significant in very weak soils, masking any measurements of friction. The unequal end area calculations for the UF penetrometers are in Appendix B.

In order to account for the pore pressure effects on the penetrometer tip joints, pore pressures can be monitored during penetration. Only weak soils are significantly affected by the unequal end area corrections, which is fortunate since less than 0.3% of the ECPT soundings in the U.S. monitor pore pressures (36,42).

As a result primarily of problems with baseline drift, compounded by questions relating to temperature compensation, unequal end area effects, and measurement design of the subtraction-type penetrometer, accurate measurements in weak soils are extremely difficult. Even with careful attention to these problems the errors in measurements may be of the same magnitude as the properties being measured. The ECPT can easily identify the soil as weak, but discrimination among various weak soils is less certain. While the electronic friction-cone penetrometer is clearly a superior instrument for "average" soils, alternate testing methods may be required to supplement the ECPT when such discrimination in weak soil is required.

CHAPTER 3
LOCAL VARIABILITY IN CONE PENETROMETER TEST MEASUREMENTS

Introduction

Variability in soil property measurements can have many sources, including measurement errors, signal noise, the innate randomness of soil (on the "micro" scale), and the spatial variability of the soil property (on the "macro" scale). The term "local variability" has been adopted to describe the point-to-point variability of a measured soil property, and encompasses the first three sources mentioned above. This differentiation is important in spatial variability studies because local variability could conceivably mask any area trends, producing inconclusive results. As an example, Baecher notes that typical measurement error variances for in situ measurements can account for 0 to 70% of the total data scatter (4). Without changes in measuring equipment and techniques, the local variability in a measured soil property must be accepted and considered in any design employing the data.

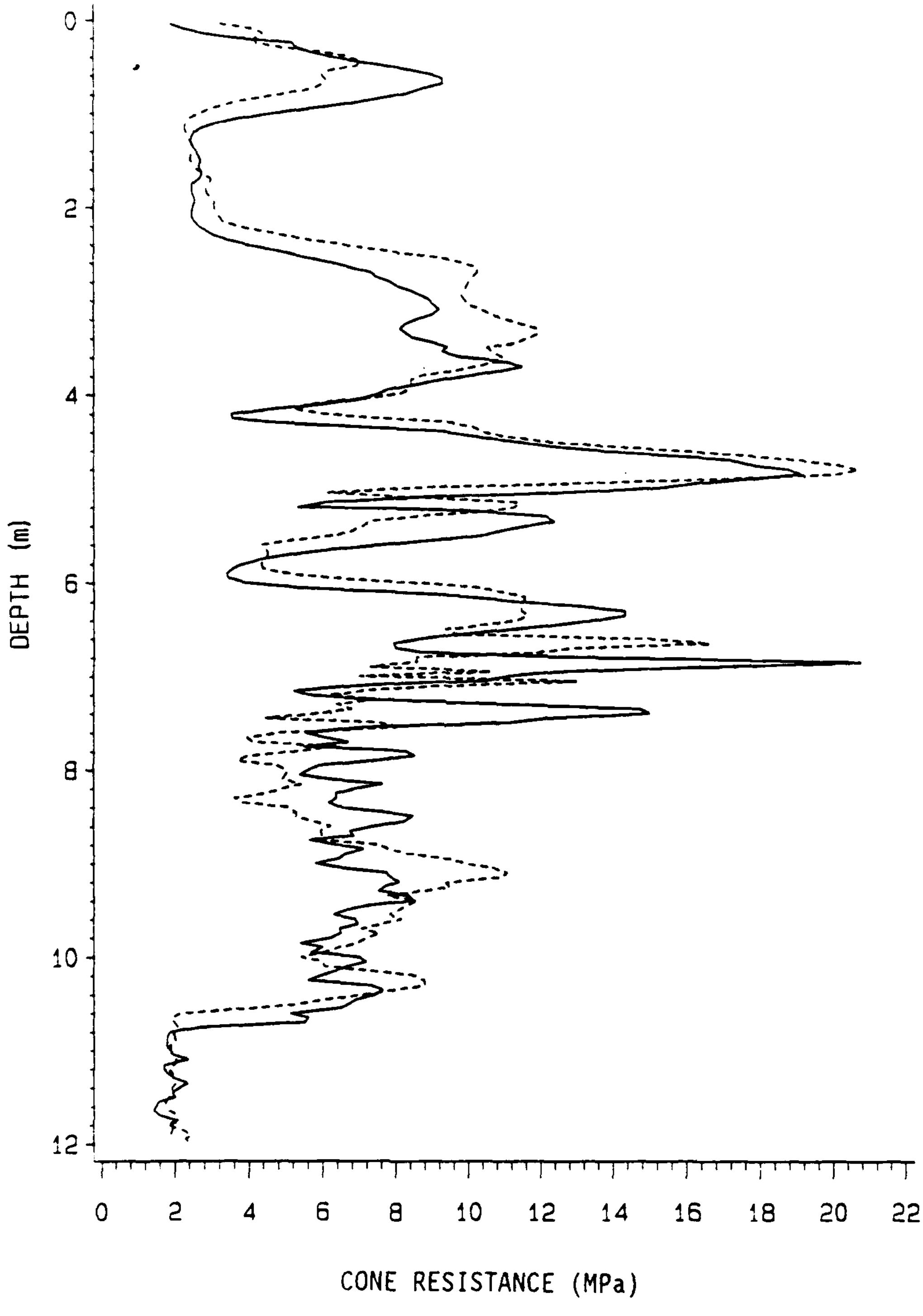
The purpose of this phase of the research is to quantify the local variability of cone penetrometer measurements used in the study. The approach used was to identify pairs of CPT soundings in the data base that were close to one another, and used the same size penetrometer. Then using graphical and statistical techniques, the local variance was described and quantified. Finally, a type of "digital filter" was devised to reduce the variance while preserving the essence of the data.

Local Variability Data Base

The research project data base was searched for pairs of ECPT soundings that met two criteria: the soundings must be no more than 4.6 meters (15 feet) apart, and the same size cone penetrometer must have been used in both soundings. The distance criteria was admittedly somewhat arbitrary, and represented an attempt to include a representative number of sounding pairs in the analysis, while hopefully insuring that the penetrometers were sampling the "same" material.

The laboratory-type requirement that the material be the same for a comparative analysis is virtually impossible to achieve in the field, making criticism a certainty. If the soundings are too close, then stress relief and other cross-hole interferences may result. If the soundings are too far apart, then "different" soils may be tested due to spatial variability. The minimum spacing was determined to be 36 cm (14 inches), based on Robertson and Campanella's recommendation of 10 hole diameters from open boreholes and excavations, to allow for potential radial stress relief effects (41). As a check on the maximum selected spacing of 4.6 meters, the sounding pairs were graphically overlaid and evaluated as to the likelihood that the material was approximately the same. If reasonable doubt existed, the sounding was discarded from further analysis. A typical comparison is shown in Figure 3-1.

The resulting data base used in the local variability study is summarized in Table 3-1, and the actual soundings are identified in Appendix A and Knox (25). Note that separation distances varied between 1.8 and 4.6 m (6 and 15 ft), and all three University of Florida penetrometer tips are represented. At the Fort Myers site, the 5-ton penetrometer tip was paired with the 10-ton tip, both of which are the



SITE = FT MYERS

Figure 3-1. Typical Matched Soundings for Local Variability Study standard 35.6 mm (1.4 inches) in diameter. A check of the results showed that the Fort Myers data fell well within scatter for all penetrometer pairs, so this pairing was judged acceptable. All other pairings involved one cone penetrometer only. For the instances where the friction baseline readings were unacceptable (as discussed in Chapter 2), only the cone resistance data were used. The designation of "Site #1" and "Site #2" was strictly arbitrary; hence any perceived skewness in the plots favoring one sounding or another could easily be reversed by simply switching the designations.

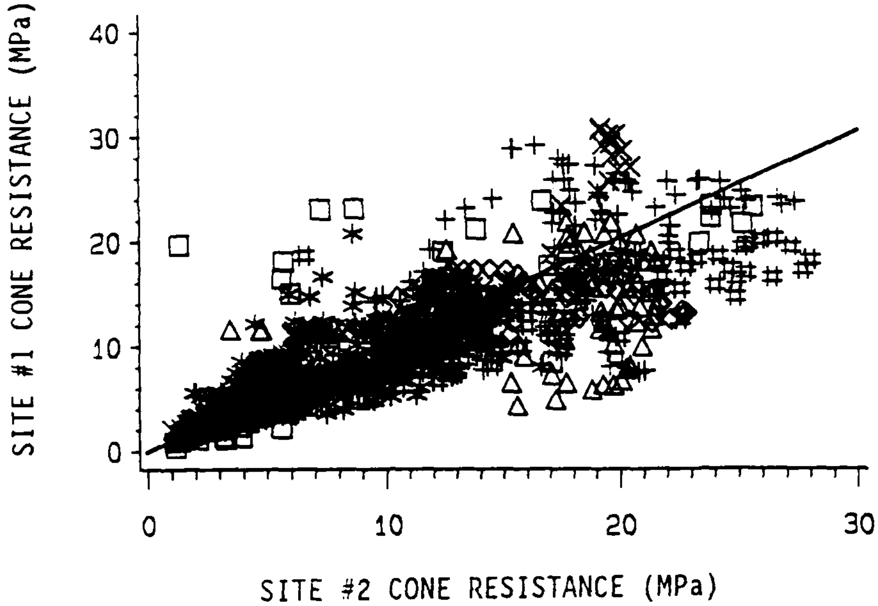
Table 3-1. Data Base for Local Variability Study

Location (ID)	Site #1	Site #2	Distance m (ft)	Penetrometer (tons)	Comments
Archer Landfill (ALFa)	C029A	C029B	3.7 (12.0)	10	
Archer Landfill (ALFb)	C029C	C029D	4.6 (15.0)	10	
Fort Myers (FMYER)	C010D	C010E	2.9 (9.5)	5/10	q_c only
Sarasota Condo (SCNDO)	C008A	C008B	2.4 (8.0)	15	
Sarasota Garage (SGARa)	C006C	C006D	1.8 (6.0)	15	
Sarasota Garage (SGARb)	C007A	C007B	2.1 (7.0)	15	
Sarasota Garage (SGARc)	C007C	C007D	2.6 (8.5)	15	q_c only

Figure 3-2, representing 1287 observations, shows the cone resistance data plotted about the expected 1:1 line. Most of the data are relatively well-behaved about the line. Figure 3-3 shows a similar plot for the friction resistance data, representing 809 observations.

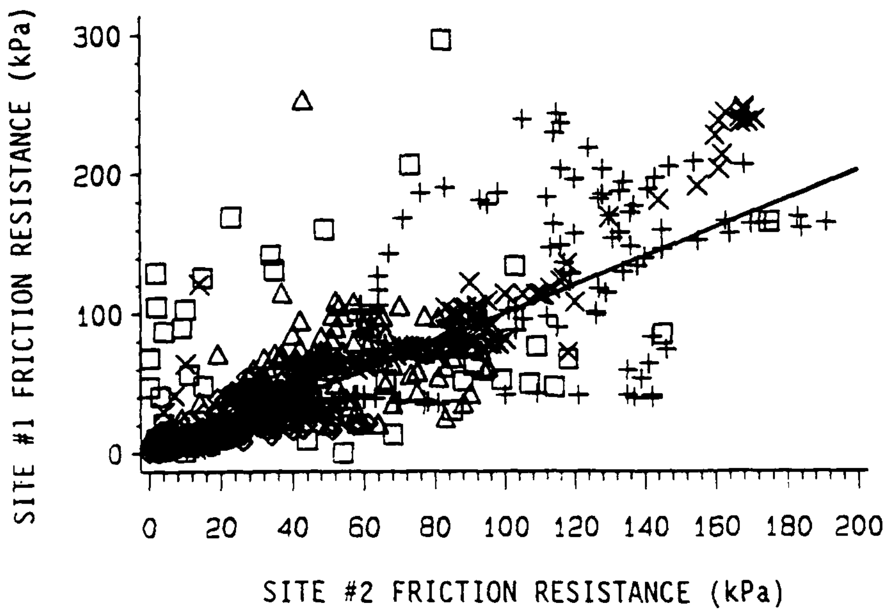
Data Filter

As can be observed in Figure 3-1, many of the large-magnitude "errors" between Soundings #1 and #2 are due to mismatches in the high-



SITE + + + ALFa × × × ALFb ✱ ✱ ✱ FMYER □ □ □ SCNDO
◇ ◇ ◇ SGARa △ △ △ SGARb # # # SGARc

Figure 3-2. Cone Resistance Data for Local Variability Study



SITE + + + ALFa × × × ALFb ✱ ✱ ✱ FMYER □ □ □ SCNDO
◇ ◇ ◇ SGARa △ △ △ SGARb # # # SGARc

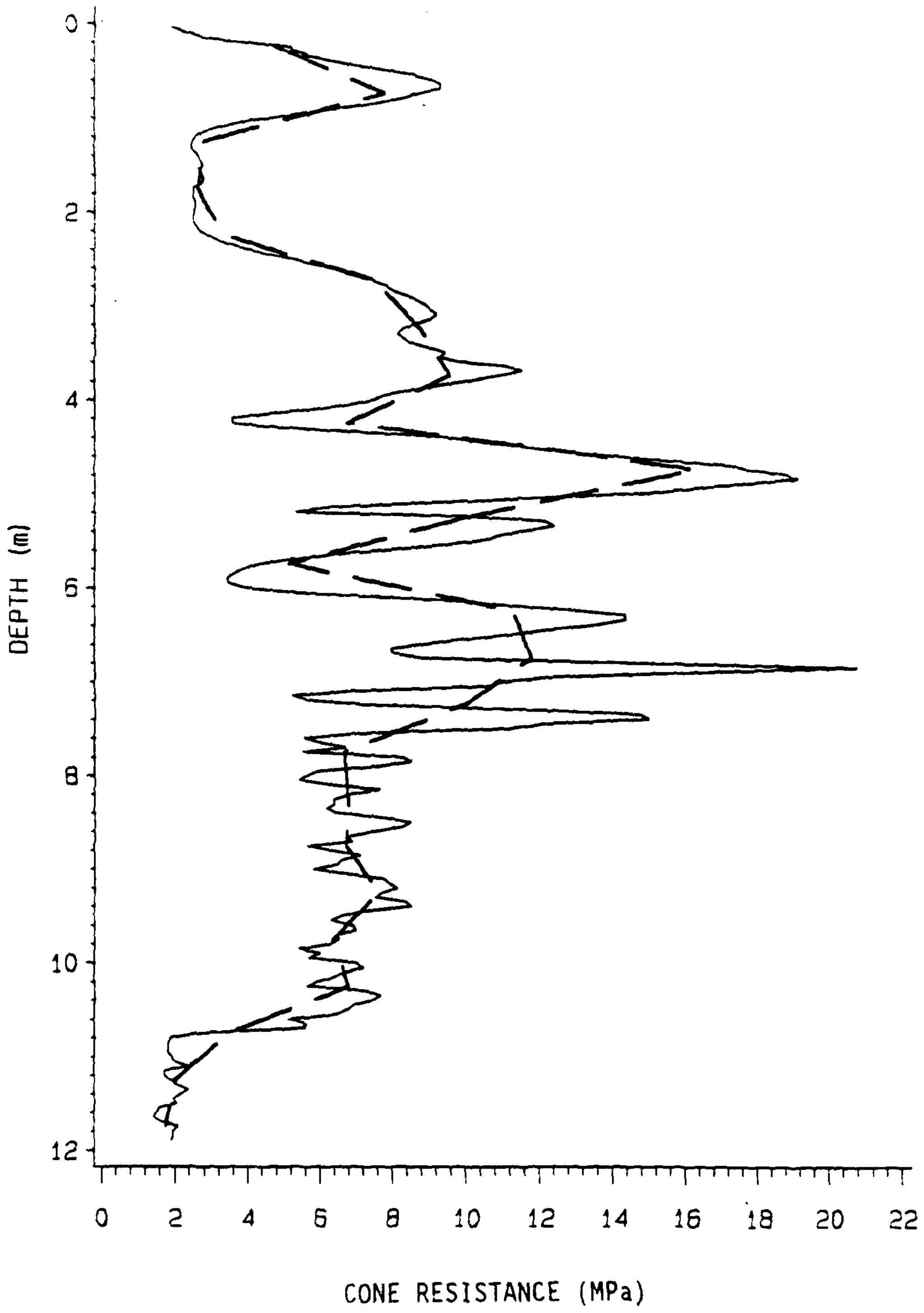
Figure 3-3. Friction Resistance Data for Local Variability Study frequency (and often high-amplitude) peaks characteristic of some soils, especially stiffer ones. These mismatches result in some of the large magnitude scatter observed in Figures 3-2 and 3-3. To reduce the influence of this high-frequency "noise" in the spatial variability study, a digital filter was sought.

Several typical digital filters were tested on sample data sets, including moving average and nonrecursive filters employing parabolic fits (24). However, either inadequate smoothing of the data occurred, or sudden shifts in the data were anticipated too early. The adopted filter used a simple average method. The data were divided into 0.5-meter (1.6-foot) increments, the average value of the increment determined, and this value assigned to the midpoint of the increment. This filter was able to smooth out the high-frequency noise in a sounding, while preserving the essence of the sounding. Figure 3-4 shows one of the soundings from Figure 3-1 before and after filtering.

Figures 3-5 and 3-6 are identical to Figures 3-2 and 3-3, except that the data have now been filtered. Note that the scatter has been reduced. The number of data points has also been reduced by a factor of 10 as a result of filtering. In computer-intensive applications where the point-to-point soil properties are not critical, such a filter can greatly reduce computer processing time and storage requirements, while, to a point, still reflect the influence of the entire (unfiltered) data set.

Evaluation of Data Scatter

To evaluate the data scatter, regression analysis using the REG procedure of the SAS system was used. The models used in the analysis were



Solid = Unfiltered   Dashed = Filtered

Figure 3-4. Effect of Average-Value Data Filter

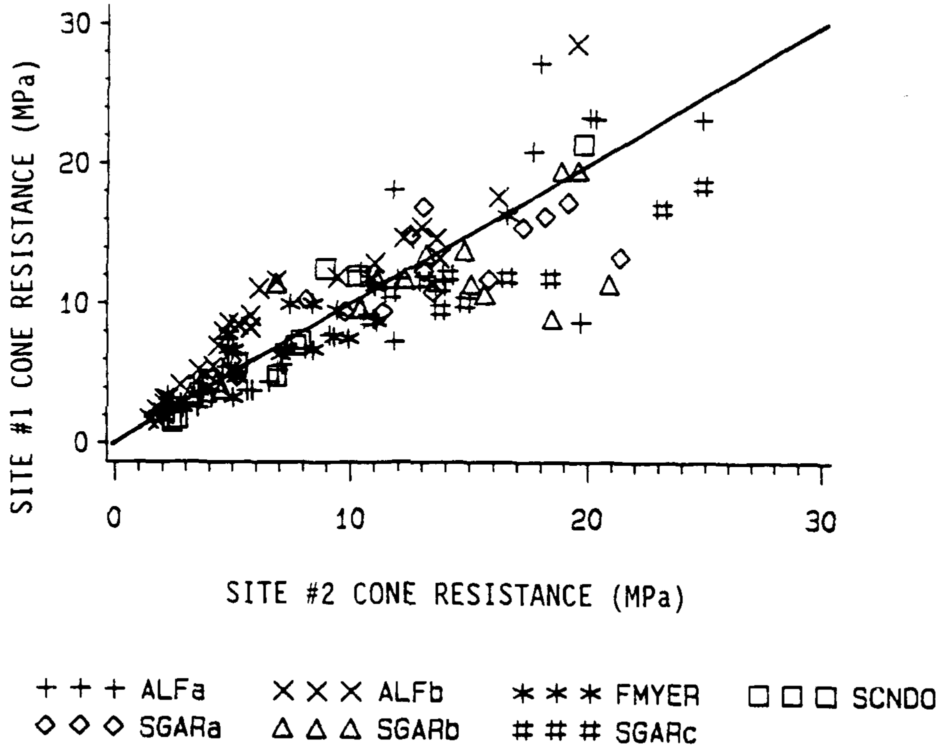


Figure 3-5. Cone Resistance Data After Data Filtering

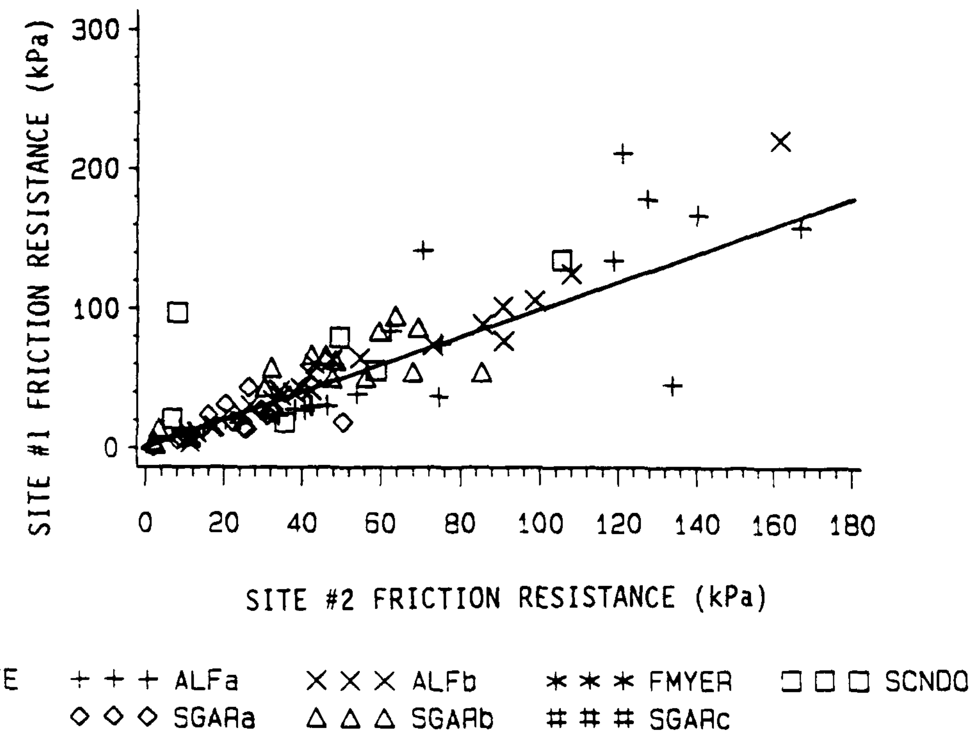


Figure 3-6. Friction Resistance Data After Data Filtering

$$(q_c)_1 = b_0 + b_1(q_c)_2 \quad \text{..........} (3\text{-}1)$$

$$(f_s)_1 = b_0 + b_1(f_s)_2 \quad \text{..........} (3\text{-}2)$$

Besides calculating a slope and intercept using the ordinary least squares approach, the REG procedure also calculates the root mean square error of the model, or RMSE:

$$RMSE = \sqrt{\frac{\Sigma(Z_A - Z_P)^2}{n - 2}} \quad \text{..........} (3\text{-}3)$$

in which n is the number of observations, Z is the soil property being measured (either q_c or f_s), and the subscripts A and P refer to actual and predicted values of the soil property, respectively. This RMSE is an unbiased estimate of the standard deviation of the errors about the regression line (9,16).

Table 3-2. Results of Local Variability Study

Parameter (units)	Filter	b_0	b_1	RMSE
Cone Resistance (MPa)	No	1.77	0.80	3.44
	Yes	1.41	0.83	2.91
Friction Resistance (kPa)	No	3.79	1.03	31.1
	Yes	0.46	1.10	23.9

From Table 3-2 one can see that using the average-value data filter reduced the root mean square error by approximately 15% for q_c, and over 23% for f_s. Thus the use of the filter appears desirable, especially when one is primarily interested in the most likely value of the soil property in question.

Based on the results of this study as summarized in Table 3-2, reasonably conservative values for the local standard deviation of friction-cone penetrometer measurements are estimated to be 3.0 MPa for q_c, and 24 kPa for f_s. Figures 3-7 and 3-8 plot the residuals from the regression analysis (Actual minus Predicted) as a function of the independent variable for q_c and f_s, respectively. Only the lower-magnitude values of the data are shown in the figures for amplification. Note that at very low values of q_c and f_s the variability is lower, increasing with increasing values of the soil property. It is proposed that the following standard deviation be adopted for the spatial variability study, as shown on Figures 3-7 and 3-8:

$$\text{local standard deviation } (q_c) = 0.5(q_c) \quad \text{for } q_c \leq 6.0 \text{ MPa (62.7 tsf)}$$
$$= 3.0 \text{ MPa (31.4 tsf)} \quad \text{for } q_c > 6.0 \text{ MPa}$$

$$\text{local standard deviation } (f_s) = 0.5(f_s) \quad \text{for } f_s \leq 48 \text{ kPa (0.50 tsf)}$$
$$= 24 \text{ kPa (0.25 tsf)} \quad \text{for } f_s > 48 \text{ kPa}$$

The local standard deviation can be interpreted as the minimum precision one can expect from the cone penetrometer measurements used in the spatial variability study. It may be argued that the variability measured in the local variability study was in reality true spatial variability. However this author contends that any variability measured over a horizontal span of less than 4.6 meters (15 feet) in what appear to be nearly identical soils is for most practical applications a "local" phenomenon, and can be treated as such.

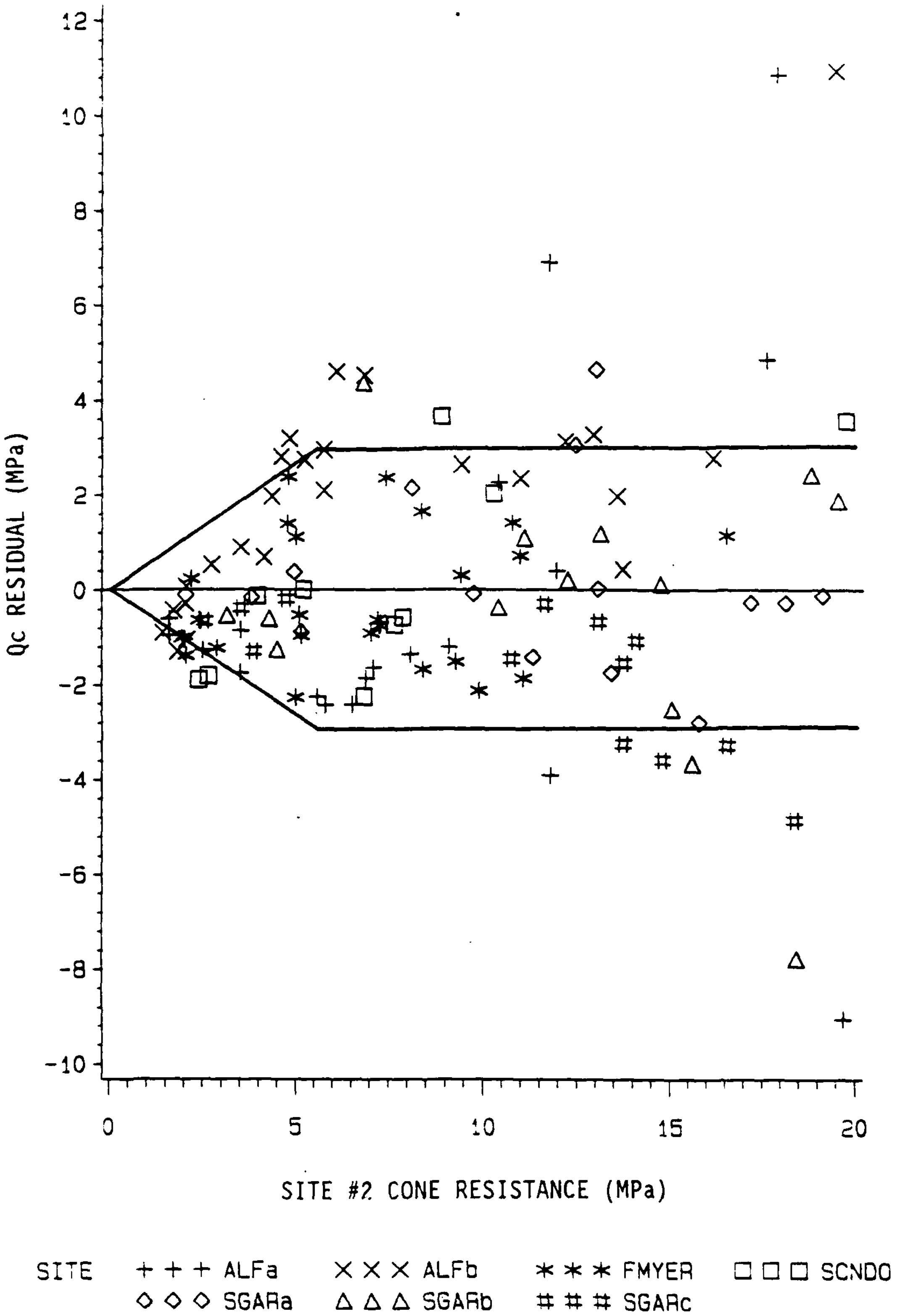


Figure 3-7. Residual Analysis and Proposed Standard Deviation for q_c

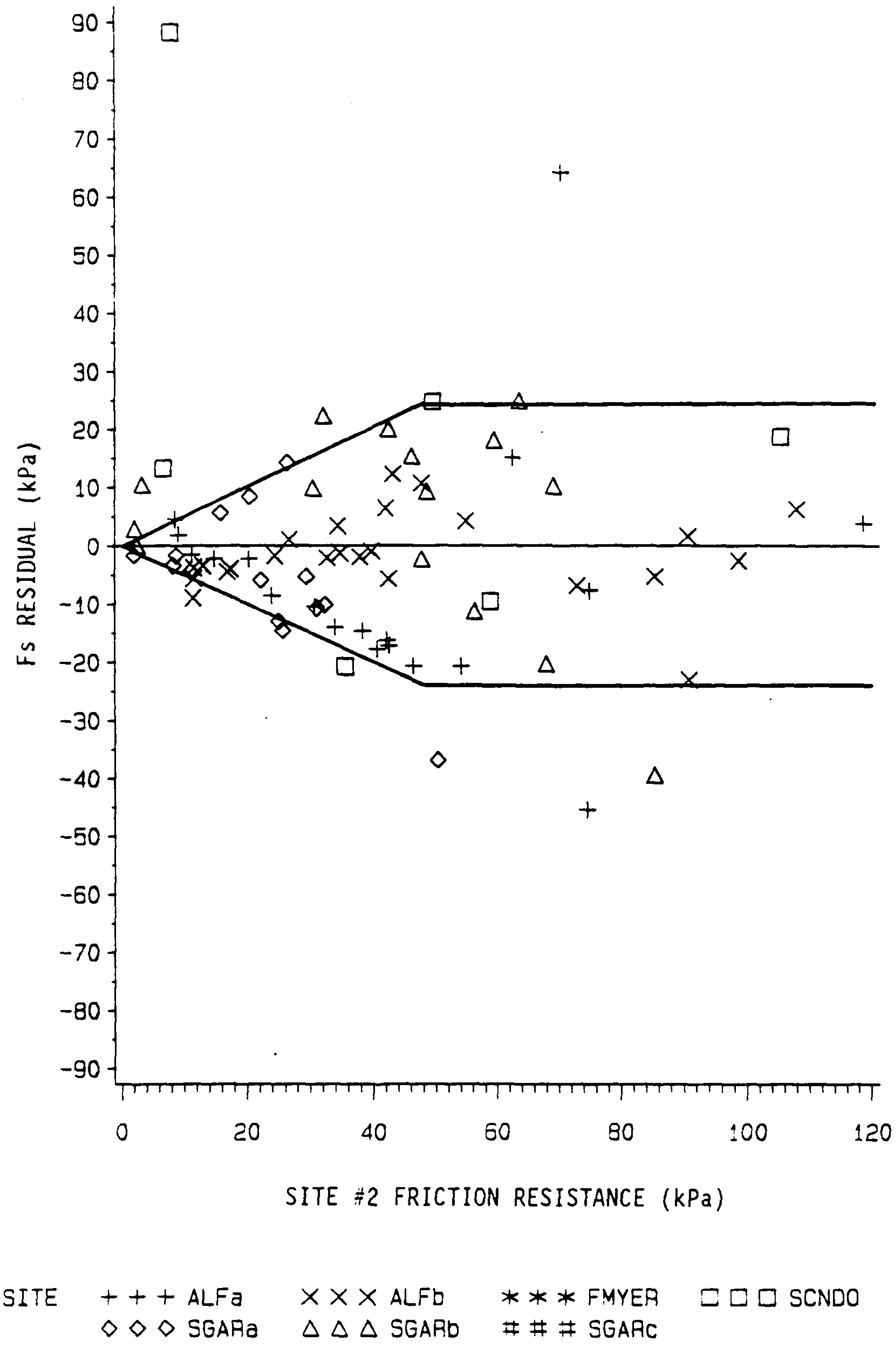


Figure 3-8. Residual Analysis and Proposed Standard Deviation for f_s

CHAPTER 4
DESCRIBING THE SPATIAL VARIABILITY OF SOILS

Introduction

Because of the way it is formed, even nominally homogeneous soil layers can exhibit considerable variation in properties from one point to another. This variation is termed spatial variability. Depending on the factors involved in soil formation (source material, transport mechanisms, etc.) and their fluctuations over both time and space, the spatial variability may be large or small. Lumb notes this variability in soil properties tends to be random, although general trends may exist both vertically and horizontally (30).

The evaluation of soil variability is important because soil properties must be estimated from a limited number of in situ and laboratory tests. When soil properties are estimated at an unobserved location, the engineer needs to have confidence that his estimates are likely to be representative of the actual soil properties at that location, or at least be able to quantify his confidence in the estimates.

In evaluating soil variability, modern statistics and data analysis offer several tools to help achieve these goals. The purpose of this phase of the research is to evaluate these tools, and to develop a field-usable methodology for describing the spatial variability of Florida soils. A word of caution is in order, however. In applying these tools one is reminded of Ralph Peck's admonition that subsurface engineering is an art--"...every interpretation of the results of a test boring and every interpolation between two borings is an exercise in geology. If carried out without regard to geologic principles the results may be erroneous or even ridiculous" (37, p.62). Fortunately most of Florida's soils are depositional due to their marine origin, somewhat simplifying the geology and aiding interpolation.

Descriptive Statistics for Spatial Variability

Summarizing a Data Set

Traditionally, a deterministic, or single-valued approach is used in describing soil properties. The most commonly used approach to quantify a measured property, x, of a nominally homogeneous soil layer is to use the average or mean value, $\bar{x}$, of the property:

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \qquad \text{(4-1)}$$

in which x_i is the measured value of the property at point i, and n is the total number of measurements. This estimator is the best choice for summarizing data if the data are normally distributed. However, this measure is sensitive to nonnormal distributions and to outliers, which are unusually high or low data points that stand out from the rest due to mistakes or other reasons.

An alternative to the mean for describing the center of a distribution is the median, defined as the middle value of a data set ordered from smallest to largest value. The median is robust against outliers, and can do a better job of summarizing nonnormal distributions.

Siegel (54) offers a compromise between the mean and median for describing a set of data, called the trimmed average. This statistic removes the extremes from a distribution, and averages the remaining data. For example, a 10% trimmed average would remove 10% of the highest values, and 10% of the lowest (rounding down when the sample size is not evenly divisible by 10), and then take the mean of the remaining 80% of the data.

Describing Variability

The uncertainty in the mean of a data set is described by its variance, V, or the square root of the variance, termed the standard deviation, s:

$$V = \frac{\Sigma(x - \bar{x})^2}{n - 1} \quad \text{.......................................}(4\text{-}2)$$

$$s = \sqrt{V} \quad \text{.......................................}(4\text{-}3)$$

For normally distributed data, approximately 68% of the data should lie within one standard deviation of the mean, and 95% within two standard deviations. As is true of the mean, the variance and standard deviation are sensitive to outliers and nonnormal distributions.

If the variance is comprised of contributions from different, uncorrelated sources (such as from spatial variability, measurement error, signal noise, etc.), then the total variance is equal to the sum of the individual variances (3,26,57,63):

$$V_T = V_1 + V_2 + \ldots + V_n \quad \text{.......................................}(4\text{-}4)$$

A more robust measure of variability, related to the median, is the interquartile range. If the data are ordered from smallest to largest, the lower quartile is the 25% value (one-fourth of the data is less than or equal to the lower quartile), the median is the 50% value, and the upper quartile is the 75% value. Therefore

$$\text{interquartile range} = \text{upper quartile} - \text{lower quartile} \quad \text{(4-5)}$$

Using tables for the area beneath a normal distribution, for normally distributed data the standard deviation and interquartile range can be related by

$$\text{interquartile range} = 1.46\ s \quad \text{(4-6)}$$

If we have a random sample from a normally distributed population, we can determine a confidence interval on the mean of the sample using the following:

$$\text{interval} = \bar{x} \pm \frac{t_{n-1}\ s}{\sqrt{n}} \quad \text{(4-7)}$$

in which t_{n-1} is called the t-value. Given the desired confidence level and the number of degrees of freedom (equal to n-1), the t-value can be obtained from standard statistical tables. Figure 4-1 shows the t-value for selected two-sided confidence intervals.

Measuring Association

If Z is a function of two variables x and y, then the strength of association between the two variables is usually measured by their correlation coefficient, r:

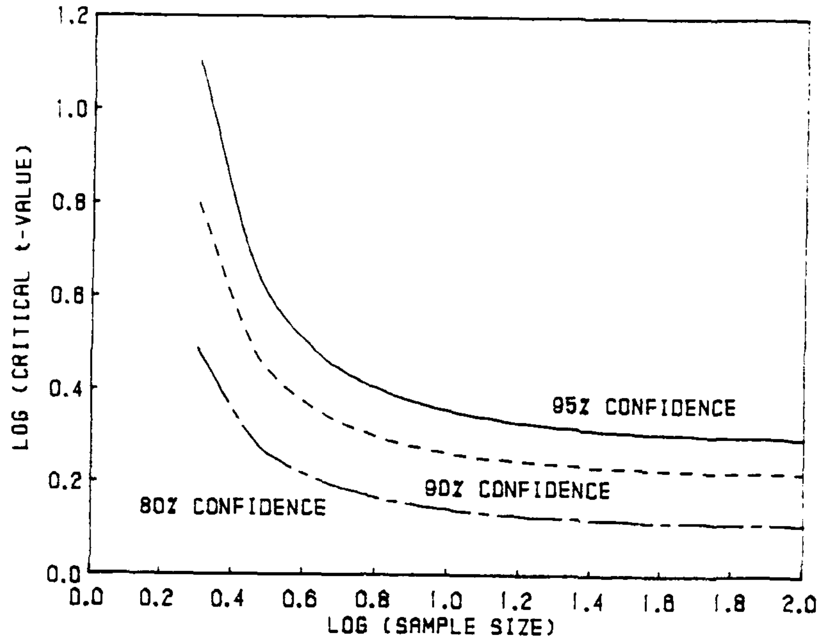
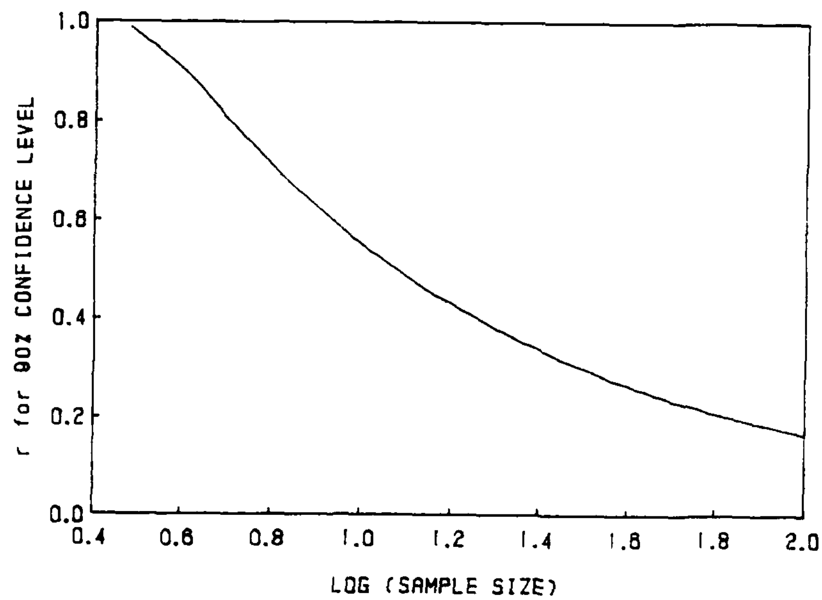


Figure 4-1. Critical t-Values for Two-Sided Confidence Intervals



Source: Siegel (1988) p.430

Figure 4-2. Critical Values for Testing Significance of Correlation Coefficient

$$r(Z) = r(x,y) \doteq \frac{\Sigma[(x_i - \bar{x})(y_i - \bar{y})]}{\sqrt{[\Sigma(x_i - \bar{x})^2][\Sigma(y_i - \bar{y})^2]}} \qquad (4\text{-}8)$$

The correlation coefficient ranges between +1 and -1, with +1 indicating perfect 1:1 correlation, 0 indicating no correlation, and -1 indicating perfect inverse correlation (i.e., as one variable increases, the other decreases proportionally). For interpreting other values of the correlation coefficient, Smith (55) suggests the following guide:

$\lvert r\rvert \geq 0.8$	Strong correlation, assume complete dependence
$0.8 \geq \lvert r\rvert \geq 0.2$	Moderate correlation
$0.2 \geq \lvert r\rvert$	Weak correlation, assume complete independence

Siegel (54) suggests minimum values of the correlation coefficient for testing that a significant association exists, given the sample size and level of confidence desired. The data must represent a random sample of the population and must be bivariate normal, meaning the two variables come from normal distributions and plot linearly (x versus y) except for randomness. These requirements rule out outliers and nonlinear data sets. Figure 4-2 is a plot of the critical r values for a 90% confidence level.

The association between the uncertainty of two variables, x and y, is usually described by their covariance, C:

$$C(x,y) = \frac{1}{n-1} \sum_{i=1}^{n} [(x_i - \bar{x})(y_i - \bar{y})] \qquad (4\text{-}9)$$

Note that when x=y, then the covariance equals the variance (i.e., the diagonal terms in a covariance matrix are the variances, V). It can also be shown that the covariance, correlation coefficient, and standard deviation are related by

$$r(x,y) = \frac{C(x,y)}{s_x s_y} \quad \ldots\ldots (4\text{-}10)$$

Estimation Models

Traditional Choices

When faced with the need for determining a soil property for input into a design process, the conventional or deterministic approach is to assume a homogeneous soil (or soil layer), described by some "average" value for the soil property. This single-value approach is appealing due to the simpler mathematics involved. If a measure of the soil's variability is also desired, the standard deviation of the measured property and perhaps a confidence interval are the usual choices.

Often, however, the variability of measured soil properties is so great that a simple "average" could result in needlessly conservative or dangerously nonconservative design. Thus explicit consideration of the spatial variability of soil is required. A model is needed which can predict a soil property at a point i, based on measurements of the property at n other points.

Some of the most commonly used estimation techniques seek to interpolate between measured points by fitting linear and higher order regression models to the data using the well-known least squares curve fitting techniques (17,26,46,58). Distance weighting functions, such as a/d and a/d^2 (where d is the distance between the measured point and the point to be estimated, and a is a suitably chosen parameter) are also often used to estimate soil parameters. Regarding the use of these models for estimating properties used in the mining industry, Rutledge criticizes these procedures as being "quite arbitrary and without a sound theoretical basis. The so-called 'principle of gradual change' and the 'rule of nearest points' are an appeal to mysticism, not science" (46, p.300). Rutledge's objections notwithstanding, these methods have been successfully used for many years in designing and constructing innumerable civil structures.

Random Field Models

In response to the need for an estimation model based at least in part on theoretical principles, numerous researchers have acknowledged the stochastic nature of soil by employing random field models to estimate soil properties (3,5,10,12,26,27,28,30,46,58,59,60,63). Generally, these models are two-part models consisting of a nonstationary and a stationary portion. The nonstationary, or trending portion of the model is generally described by conventional regression analysis. The random field models are used for the stationary, or stochastic portion (i.e., the residuals from the regression analysis). The stationary portion of the model attempts to improve the soil property prediction from the regression analysis (the nonstationary portion) by considering any correlation structure within the residuals. This correlation structure (more properly termed autocorrelation) results from the fact that nearby soil volumes tend to have similar residuals from the regression analysis (i.e., adjacent soil volumes would both tend to be above or below the prediction from regression, whereas more distant soil volumes would more likely follow the expected random variation about the regression prediction).

Figure 4-3 describes the Random Field Model concept. While the straight line (determined from regression analysis) predicts the general trend of the data, knowledge of Points #1 and #2--which are correlated with one another--would permit a better prediction of Point #3, thus enhancing the prediction from the regression model.

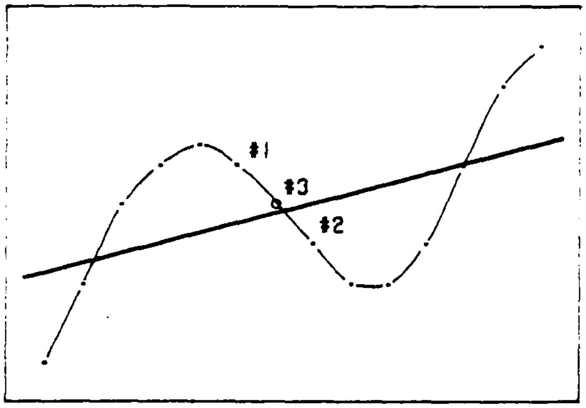


Figure 4-3. Random Field Model Concept

Regression analysis. In using the ordinary least squares (OLS) approach to regression analysis, the model used is typically

$$[Z] = [X][b] + [e] \qquad (4\text{-}11)$$

in which

$[Z]$ = $(n \times 1)$ column vector of n observations of the dependent variable Z

$[X]$ = $(n \times p)$ matrix comprised of 1's in the first column to represent the intercept term b_1 (i.e., $X_1 = 1$), and of the n observations on $(p - 1)$ independent variables $X_2, \ldots, X_p$

[b] = (p x 1) column vector of unknown weights to be determined: b_1 (the intercept term), $b_2, \ldots, b_p$

[e] is an (n x 1) column vector of n residuals, e_i

Several key assumptions are made relative to the residual terms in applying the OLS method to regression analysis, namely that they have zero mean, are uncorrelated, have constant variance, and are normally distributed (14). These assumptions are often represented by

$$e = N(0,V) \quad \text{(4-12a)}$$

$$E[C(e_i,e_j)] = 0 \quad \text{for } i \neq j \quad \text{(4-12b)}$$

in which E[ ] is the expected value of [ ].

As introduced above, though soil is typically considered a random media, soil properties for neighboring soil volumes tend to be more correlated than the properties for more distant volumes, causing the covariance assumption (Equation 4-12b) to be violated for some $i \neq j$. This feature is termed autocorrelation. The random field models attempt to improve soil property estimation by accounting for the autocorrelation structure of the residuals.

<u>Autocorrelation structure</u>. Autocorrelation structure is often described by a semi-variogram (Figure 4-4), which is a graph showing the degree of continuity of a soil property (26,33,40). By graphing the semi-variogram function, $\gamma(r)$, against separation or lag distance, r, the semi-variogram provides information on how far data may be spatially extrapolated (4). The theoretical semi-variogram function is equal to

$$\gamma(r) = 0.5\ V\ [Z(x + r) - Z(x)] \quad \text{(4-13)}$$

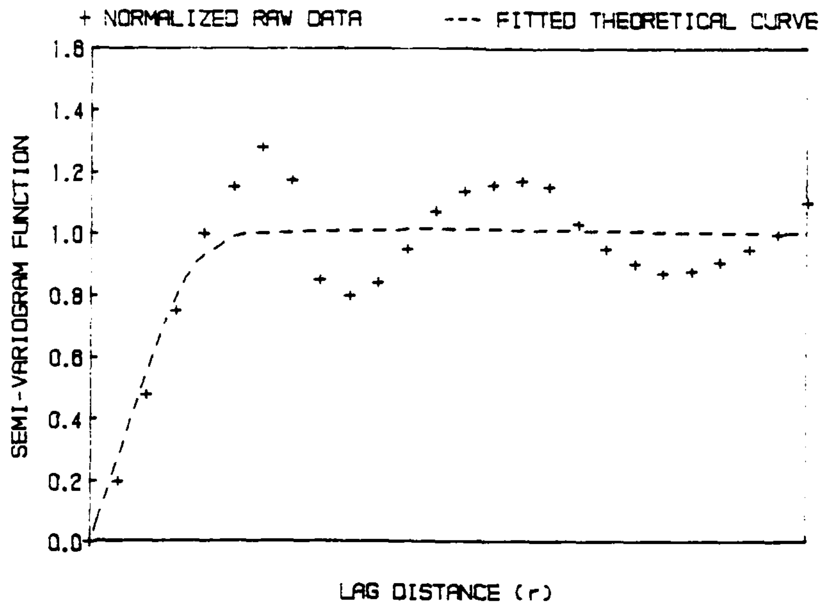


Figure 4-4. Typical Experimental Semi-Variogram of Normalized Data

in which Z(x) is the value of property Z at point x and V[] is the variance. For random residuals this function will level off to a constant value (the variance of the data set) at r greater than a distance termed the range of the variogram. For finite data sets, Equation 4-13 is estimated by

$$\gamma(r) = \frac{1}{2N(r)} \sum_{i=1}^{N(r)} [Z(x_i + r) - Z(x_i)]^2 \qquad (4\text{-}14)$$

in which N(r) is the number of observation pairs whose separation distance is r. In working with real data spaced at less than uniform intervals, a band or tolerance is often applied to the separation distance (i.e., r = 50 feet $\pm$ 10 feet). Tang (59) cautions that the error in the estimated variogram can be substantial if r varies significantly from the discretized average distance. Also, the reliability of the estimate for $\gamma(r)$ decreases with increasing r, so usually only separation distance values up to one-fourth to one-half the total distance spanned are used in the analysis (26,28).

Vanmarcke (63) notes that statistical analysis of actual soil data can often be handled easier if the soil is normalized to be "statistically homogeneous," producing what Lumb calls a "grossly uniform soil" (31). Data can be normalized to have a mean of zero and a standard deviation (and variance) of unity by the following transformation:

$$x_n = \frac{x - \bar{x}}{s_x} \quad \text{(4-15)}$$

where x_n is the normalized data corresponding to x. For normalized random data, the semi-variogram function should level off to a value of one.

Given a data set of normalized residuals, the autocorrelation function, $\rho(r)$, is complementary to the semi-variogram function, and can be determined by

$$\rho(r) = 1 - \gamma(r) \quad \text{(4-16)}$$

Similar to the correlation coefficient, $\rho(r)$ can vary between 1 (perfect continuity of the soil property) and 0 (completely random variation). However, as a measure of association between data pairs, the correlation function may seem more familiar to engineers than the semi-variogram function, whose origin lies in mining geology. Figure 4-5 shows the correlation function corresponding to Figure 4-4, and fitted by an

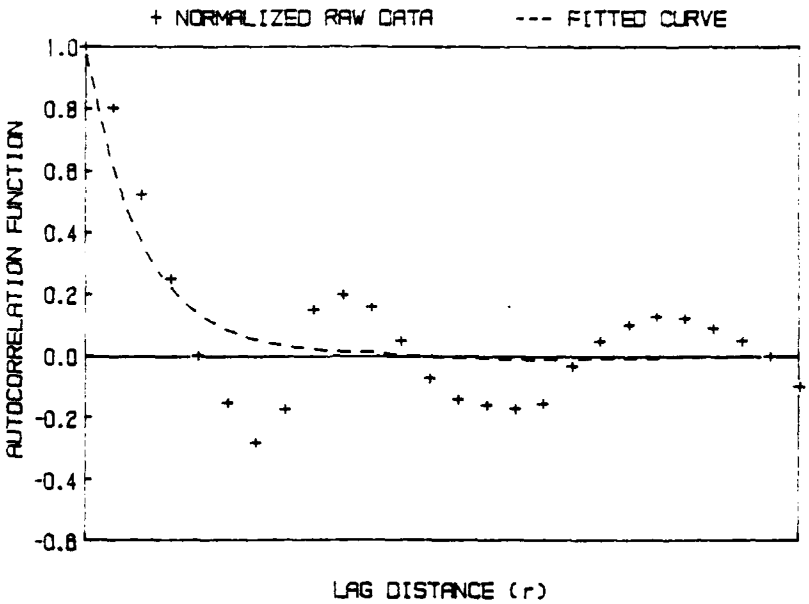


Figure 4-5. Typical Experimental Autocorrelation Function

exponential expression from Vanmarcke (63). Vanmarcke presents four analytical expressions of many in the literature describing the correlation function, each characterized by a single parameter. He notes that all of the formulas are merely curve fitting expressions with no theoretical basis; hence, they all "work" about equally well--a practical point of view echoed by Tang (59).

The correlation function (or the related semi-variogram) is used to account for autocorrelation structure in regression analysis, as described below. It is also a powerful device for estimating the maximum spacing between samples. In order to characterize the autocorrelation structure of a site (and, hence, the spatial variability of the measured soil property), Peters (40) states the maximum spacing between samples is the range of the variogram (or correlation function), with a recommended spacing of two-thirds to three-quarters of the range. A larger spacing would likely miss the correlation structure, and a smaller spacing would be unnecessarily expensive. Naturally, closely-spaced trial samples in the area would be initially required to establish the correlation structure of the soil property. Kulatilake and Miller note that if the purpose of a site investigation is to generally characterize the site while avoiding redundancy (i.e., to describe the general trend of the site), then sample spacing should be greater than the range (27).

Incorporation into model. If the nonstationary portion of the regression model is designated Z^*, and the stationary portion Z^{**}, then the complete model is

$$Z(x_i) = Z^*(x_i) + Z^{**}(x_i) \qquad \text{(4-17)}$$

in which $Z(x_i)$ is the estimated value of the soil property, Z, at point x_i. The nonstationary portion is estimated using conventional regression techniques. The stationary portion is estimated using a method presented by Kulatilake and Ghosh (26).

One of the difficulties in applying a random field model is testing for stationarity of the data. Normally replicate testing techniques can be used to insure that the residuals are N(0,V) beyond the range of the semi-variogram; but with destructive tests such as the CPT and SPT, alternate methods are required. Kulatilake and Ghosh proposed examining the form of the semi-variogram at large lag distances. If the normalized semi-variogram function levels off to 1 (or the complementary autocorrelation function to 0), then stationarity can be assumed. However, if leveling-off behavior is not exhibited, then a trend component is apparently remaining in the residuals, and a higher order regression model should be used. They recommend using the lowest order trend (nonstationary) model that results in a satisfactory semi-variogram.

In quantifying the stationary portion of the estimation model, Kulatilake and Ghosh employed an approach related to the geostatistical procedure called kriging. Briefly, kriging is a computer-intensive process used to estimate the value of an unknown, autocorrelated property using a linear weighting function. The weights are chosen subject two conditions: the sum of the weights must equal 1, and the sampling variance should be minimized (4,6,10,12,33). $Z^{**}(x_i)$ was thus estimated by

$$Z^{**}(x_i) = (s_e) \sum_{k=1}^{q} a_{ki} h_k \quad \ldots\ldots (4\text{-}17)$$

$$a_{ki} = \frac{\rho_{ki}}{\Sigma \rho_{ji}} \quad ; \quad j = 1,2,\ldots,q \quad \ldots\ldots (4\text{-}18)$$

in which

q = the number of measurements within the correlated region around x_i

s_e = the standard deviation of the residuals from lowest order regression model resulting in stationary autocorrelation function

h_k = the normalized residual at location k within the correlated region about point i

a_{ki} = a suitable weighting coefficient, and

ρ_{mn} = value of the correlation function for a separation distance corresponding to the distance between points m and n

CHAPTER 5
EVALUATION OF THE SPATIAL VARIABILITY MODELS

Application of Estimation Models

Five general models for predicting soil properties influenced by spatial variability were evaluated at three sites, as discussed below. In all cases the approach taken was to attempt to predict a sounding (whether it be an SPT or CPT sounding) by suppressing that sounding from the data base, and using the remaining soundings for the prediction. The three sites selected were Choctawhatchee Bay (CPTs), Apalachicola River (SPTs), and Archer Landfill (CPTs).

Evaluation Criteria

The root mean square error, RMSE, was used as a criterion to evaluate the accuracy of the various models. The model to predict a soil property, Z, which minimizes the RMSE can likely be judged the best of the evaluated models:

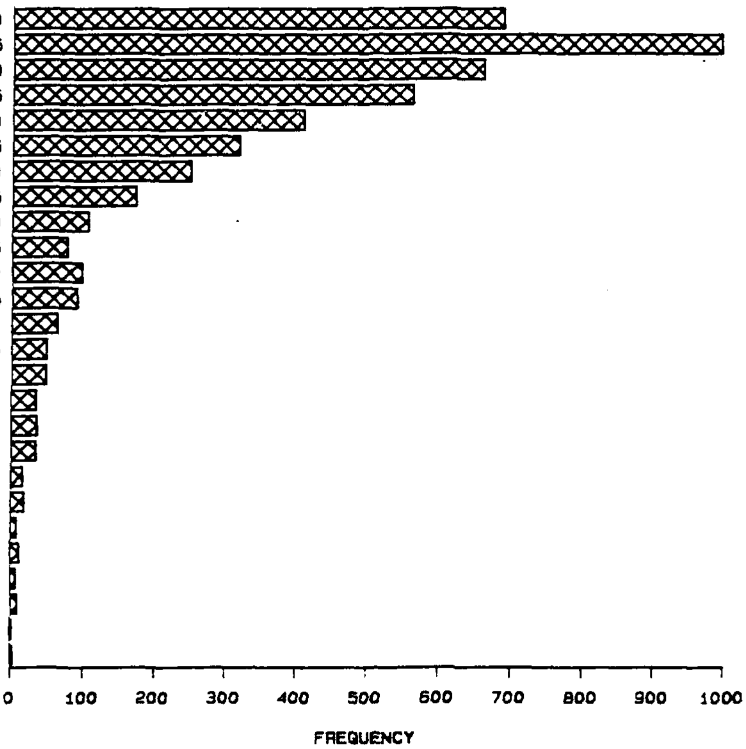
$$RMSE = \sqrt{\frac{\sum_{j=1}^{n} (Z_A - Z_P)_j^2}{n}} \qquad (5\text{-}1)$$

in which n is the number of observations, and the subscripts A and P refer to actual and predicted values of the soil property, respectively. The RMSE is an estimate of the standard deviation of the errors about the prediction; however it is not a true unbiased estimate (as was used in Chapter 3 to evaluate the local variability of cone penetration test measurements) because the denominator equals the total number of observations, not the number of independent observations. This slightly revised definition of the root mean square error is deliberate to permit true comparison between all of the prediction methods--the affect on the value of the RMSE will be negligible due to the large number of observations involved.

In addition to the RMSE criterion, the predictions were graphically overlaid onto the actual soundings and subjectively compared. This was an important check on the root mean square error to insure that the best RMSE did indeed reflect the best prediction.

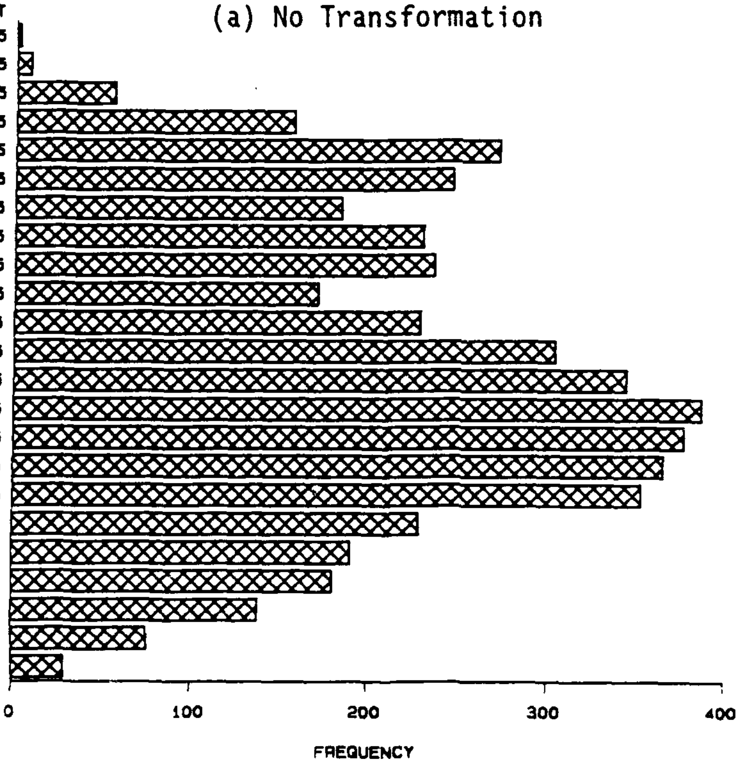
Data Manipulation

For the Choctawhatchee Bay and Apalachicola River sites, the five general models were applied to both transformed and nontransformed variables. Only transformed variables were used at the Archer Landfill site. The transformation used was logarithmic (base 10), which has the effect of spreading out small values of the variable while bringing in large values. This was judged potentially beneficial for the Florida data sets used in this analysis because of the relatively large percentage of small values of the variables (whether they be q_c, f_s, or N), and the large-valued spikes in some of the soundings. It was felt that such a transformation may emphasize the smaller values of the variables, giving a somewhat more conservative estimate. Another potential advantage of the logarithmic transformation was the elimination of any negative predictions, an occasional problem with the regression models. Figure 5-1 compares a typical frequency distribution



QC MIDPOINT	FREQ.	PCT.	CUM. PCT.
0.0	689	14.46	14.46
1.5	996	20.90	35.36
3.0	660	13.85	49.21
4.5	562	11.79	61.01
6.0	409	8.58	69.59
7.5	318	6.67	76.26
9.0	249	5.23	81.49
10.5	172	3.61	85.10
12.0	105	2.20	87.30
13.5	77	1.62	88.92
15.0	96	2.01	90.93
16.5	90	1.89	92.82
18.0	63	1.32	94.14
19.5	48	1.01	95.15
21.0	47	0.99	96.14
22.5	35	0.73	96.87
24.0	36	0.76	97.63
25.5	34	0.71	98.34
27.0	16	0.34	98.68
28.5	19	0.40	99.08
30.0	8	0.17	99.24
31.5	13	0.27	99.52
33.0	7	0.15	99.66
34.5	9	0.19	99.85
36.0	3	0.06	99.92
37.5	4	0.08	100.0

(a) No Transformation



QC MIDPOINT	FREQ.	PCT.	CUM. PCT.
-0.65	2	0.04	0.04
-0.55	8	0.17	0.21
-0.45	55	1.15	1.36
-0.35	157	3.29	4.66
-0.25	272	5.71	10.4
-0.15	246	5.16	15.5
-0.05	184	3.86	19.4
0.05	230	4.83	24.2
0.15	236	4.95	29.2
0.25	171	3.59	32.8
0.35	229	4.81	37.6
0.45	304	6.38	43.9
0.55	344	7.22	51.2
0.65	387	8.12	59.3
0.75	377	7.91	67.2
0.85	365	7.66	74.9
0.95	353	7.41	82.3
1.05	229	4.81	87.1
1.15	191	4.01	91.1
1.25	181	3.80	94.9
1.35	139	2.92	97.8
1.45	76	1.59	99.4
1.55	29	0.61	100

(b) Logarithmic Transformation

Figure 5-1. Effect of Data Transformation on Cone Resistance Data at Choctawhatchee Bay Site of a variable with its associated transformation. While neither distribution is statistically "normal," the transformed variable is much more symmetrical, suggesting that deterministic estimates of the distribution (i.e., the mean and median) may be more representative of the entire data set.

In addition to the logarithmic transformations, the cone penetration test data were filtered using the average value over a 0.5 meter increment. As discussed in Chapter 3, this digital filter smoothes out the high-frequency noise seen in many CPT soundings, while preserving the true character of the sounding. As a result the RMSE will be reduced, and will better reflect the standard deviation in the average value of the estimate.

Autocorrelation Function

As suggested by Anderson et al., the autocorrelation function was estimated for each site by considering the measured soil property values along lines of constant elevation, and pooling vertically (3). The lowest order regression model which demonstrated stationary residuals (using Kulatilake and Ghosh's approach) was used to remove the trend component. Then an equation was fitted to the autocorrelation function exhibited by the residuals. Appendix E contains two BASIC programs for calculating the autocorrelation function: one assuming the soundings are equally spaced, the other assuming irregular spacing.

As mentioned above, the autocorrelation function permits rational evaluation of the spacing of soundings during a geotechnical site investigation. Also, two of the estimation models employed in this study make use of the information obtained from the autocorrelation function; specifically the range or correlated distance, and the fitted autocorrelation function. As noted earlier, since the exact form of this equation is of little real significance and has no theoretical basis, a simple exponential form was used for each site:

$$\rho(r) = e^{-r/\beta} \qquad (5\text{-}2)$$

in which r is the lag or separation distance, and β is the constant which causes the function to best fit the actual data. The range of the autocorrelation function is the distance at which the data become uncorrelated. For the purposes of this research project, data were assumed uncorrelated when the correlation coefficient was approximately 0.1 or less.

Model Types

Deterministic. A constant value was used to represent the soil for the whole depth. Three deterministic models were evaluated: the mean, the median, and the 10% trimmed average of the entire data set.

Distance Weighting. Two distance weighting functions were applied to soundings within the range of the sounding to be predicted. The first used a_1/d for the weighting function, whereas the second function used a_2/d^2, where d is the horizontal distance from the sounding in the data base to the sounding to be predicted. The "a_n" terms were determined so that the sum of the weighting functions equaled 1:

$$a_1 = \frac{\prod_{i=1}^{n} d_i}{\sum_{i=1}^{n} \left[\prod_{i=1}^{n} d_i / (d_i) \right]} \qquad (5\text{-}3)$$

$$a_2 = \frac{\prod_{i=1}^{n} d_i^2}{\sum_{i=1}^{n} [\prod_{i=1}^{n} d_i^2/(d_i^2)]} \qquad (5\text{-}4)$$

in which d_i is the distance to sounding i of n total soundings within the range about the sounding to be predicted. If individual observations of a particular sounding were missing for some reason, then the weights were recalculated using the remaining soundings within the correlated region.

Regression Analysis. The third general model evaluated was regression analysis, which fits the "best" curve through the given data by minimizing the squared distance between the curve and the data points using the method of least squares. The adequacy of the model fit is usually summarized using the squared multiple correlation coefficient, R^2:

$$R^2 = 1 - \frac{\Sigma(Z_A - Z_P)^2}{\Sigma(Z_A - \overline{Z})^2} \qquad (5\text{-}5)$$

in which the subscripts A and P refer to actual and predicted soil property values. The R^2 value represents the proportion of the total variability in the dependent variable that can be explained by the regression model, and can vary between 0 (no fit) to 1 (perfect fit). As a rule of thumb, Brook and Arnold recommend an R^2 of at least 0.5 in order to have much confidence in the model (9).

Several levels of regression analysis were used. The lowest level, termed Model 1, was a simple first order (linear) model:

$$P = b_0 + b_1X + b_2Y + b_3Z + e \quad \text{(5-6)}$$

in which P is the predicted value, X and Y are perpendicular horizontal distances, and Z is the vertical depth from some selected reference point. Model 2 was similar to Model 1, except that a second order depth term was added:

$$P = b_0 + b_1X + b_2Y + b_3Z + b_4Z^2 + e \quad \text{(5-7)}$$

The remaining two levels of regression analysis are termed "Low Term Regression" and "High Term Regression," terminology which requires some explanation. To better describe observed trends in the data set, higher order variables are often required. However, part of the difficulty in applying regression analysis to a problem is determining which variables are important and significant in describing the trends. A stepwise variable selection technique, contained in the SAS procedure STEPWISE, was employed for selection of significant higher-order regression variables.

The stepwise technique is a well-regarded variable selection method, the details of which can be found in many texts on regression or multivariate analysis (14,16,48,56). Briefly, the stepwise procedure enters and removes predictors one by one until some "best" regression equation is found. The method starts out by entering the variable most highly correlated with the dependent variable (i.e., the predictor having the largest squared correlation coefficient--squared to allow for significant negative correlations). Succeeding variables are added at each step according to the largest F-value, a statistic which measures whether a variable's contribution to the model was significant, or could be explained by chance. A significance level of 0.15 was used to admit predictor variables to the model (meaning there was at most a 15% chance that the variable's contribution was due to chance). After a variable is admitted to the model, all previously admitted variables are then checked for possible removal by calculating their F-values, assuming that they were the last variable admitted to the model. This test eliminates predictors that may be highly correlated with subsequently entered predictors. A significance level of 0.15 was also used to remove variables. The stepwise procedure continues until all variables meeting the required F-value are entered into the model.

Lumb (30) and Tabba and Yong (58) note that horizontal trends can generally be described using first or second order variables, whereas depth variables often must be of much higher order. Therefore the variables selected for evaluation by the STEPWISE procedure were depth up to order 8, horizontal distance up to order 2, and depth-distance interaction terms up to order 5 for depth and order 2 for distance. After the STEPWISE procedure completed its analysis, the "High Term Regression Model" was the final step in the procedure, and represented the best model (as measured by the R^2 statistic) containing all predictor variables significant at the 0.15 level. The "Low Term Regression Model" was a model from one of the earlier steps in the STEPWISE procedure with an R^2 statistic nearly as large as the High Term Model (i.e., subsequent steps reflected the Law of Diminishing Returns in improvement of the model fit).

Random Field. The fourth type of model evaluated for predicting soil properties is the random field model. The nonstationary, or trend portion of the model is the lowest order regression equation exhibiting stationary residuals, as determined during evaluation of the autocorrelation function. The stationary, or random portion employs Equations 4-17 and 4-18, using the equation for the fitted autocorrelation function determined above. A BASIC program for calculating the stationary portion of the model is contained in Appendix E.

Linear Interpolation. The final general model evaluated in this study was a simple linear interpolation model. For this model, the sounding to be predicted was linearly interpolated from the immediately adjacent soundings, based on separation distance. This model provides an important comparison for the more "sophisticated" attempts to improve on a single-value (deterministic) estimate, because it is the method most likely to be employed by an engineer.

Sites Investigated

Choctawhatchee Bay. The first site evaluated was a portion of a replacement bridge being built by the Florida Department of Transportation (FDOT) across Choctawhatchee Bay in the Florida panhandle. Twelve friction-cone penetrometer soundings were used, running generally south to north between Stations 110+88 (Sounding A) and 119+47 (Sounding L) on the causeway south of the main channel, a distance of 859 feet. Figure 5-2 shows a plan view of the site. For purposes of evaluating their spatial variability, the twelve soundings were assumed on a straight line (reducing the problem to a two-dimensional problem), except that the autocorrelation function was calculated based on true separation distances. Three soundings were "predicted," located at Stations 114+78 (Sounding E), 117+00 (Sounding H), and 119+00 (Sounding J).

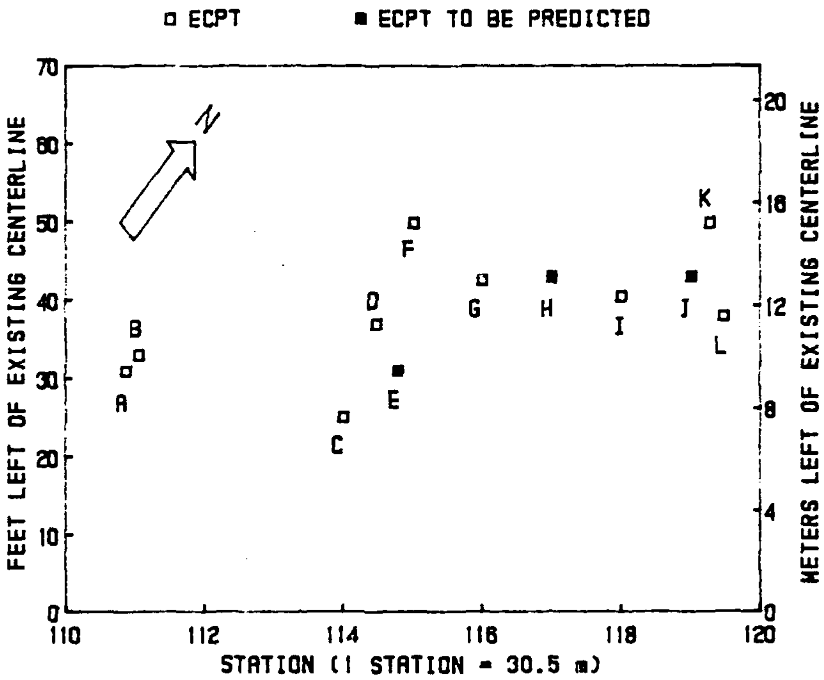


Figure 5-2. Spatial Variability Soundings at Choctawhatchee Bay

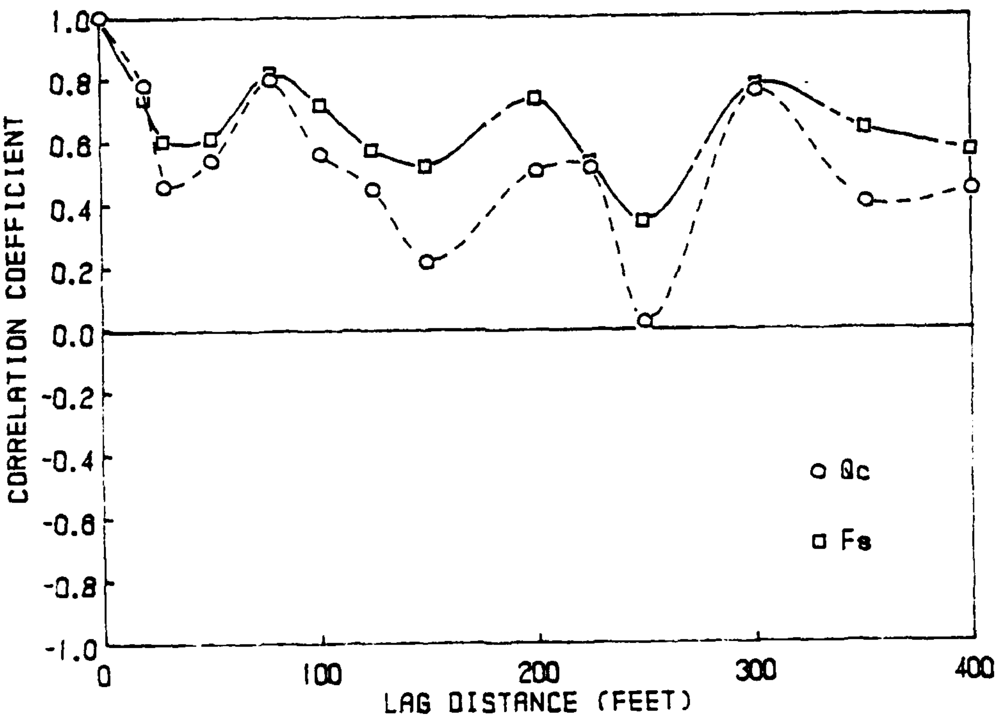


Figure 5-3. Autocorrelation Function for Normalized Raw Data at Choctawhatchee Bay

The spatial variability analysis was based on the upper 20 meters of soil. The surface elevation was nearly level at approximately 1.8 m MSL (6.0 ft MSL), with a range of 1.6 m to 2.1 m (5.4 ft to 7.0 ft). The soil is predominantly fine sand and silty sand, with some sandy clay layers.

The ECPT soundings show the site, in general, to have low to moderate q_c values to a depth of 5-7 meters (16-23 feet), followed by very low q_c's. Between 11 and 14 meters (36-46 feet) the cone resistance increases somewhat, becoming moderate to high at depths ranging from 13 to 17 meters (43-56 feet). The friction resistance values remained low throughout the soundings, increasing modestly when the stiffer sand layer was encountered. A subjective evaluation of the site would describe it as reasonably uniform, sounding to sounding. Figure 5-3 is the autocorrelation function for the raw data (normalized using equation 4-15). Autocorrelation was assumed to be a circular function in the horizontal plane (i.e., autocorrelation in the x-direction = autocorrelation in the y-direction). Figure 5-3 supports the subjective description of "reasonably uniform" since it generally leveled off to an average correlation coefficient of around 0.5 to 0.6 for at least 122 meters (400 feet) laterally.

Several of the soundings recorded negative friction values in very weak soils, a problem discussed in Chapter 3. Friction resistance values less than -10 kPa (-105 tsf) were deleted from the data base; all other negative friction values were forced to zero (Note: These values were forced to 1 kPa for the transformed f_s).

Apalachicola River. The second site evaluated for spatial variability was another FDOT bridge project across the Apalachicola

River. Thirteen standard penetration test (SPT) soundings were used, running on a line east to west between Stations 105+00 (Boring 10) and 124+00 (Boring 22) within the boundaries of the Apalachicola River. Figure 5-4 shows a plan view of the site. Three soundings were "predicted," located at Stations 106+00 (Boring 11), 114+00 (Boring 9), and 118+00 (Boring 13).

The spatial variability analysis was based on the SPT soundings between elevation -9.1 and -27.4 meters (-30 and -90 feet) MSL. To facilitate the analysis, the individual soundings were slightly adjusted up or down so that the SPT N values (with units of blows per foot) occurred at the same elevation for all soundings. The decision to limit the analysis to elevations between -9.1 and -27.4 meters was due to

1. The SPT measurements display nearly perfect uniformity from the mud line to elevation -9.1 m (with an N=1-2), and hence show virtually no detectable spatial variability; and

2. Data are sparse below elevation -27.4 m.

To minimize any undue effect of individual large data values on the analysis, all N values in excess of 150 (such as 50 blows per 3 inches, equivalent to 200 blows per foot) were truncated to 150 blows per foot. This was the only filtering performed on the Apalachicola River data set.

The soil profile is typically loose clayey sand overlying stiff clay, which overlies dense sand. The SPT soundings show the site, in general, to have low N values between elevation -9.1 and -27.4 meters (-30 and -13.7 feet). Between elevation -13.7 and -27.4 meters (-45 and -90 feet), however, the N values range widely. Adjacent soundings tended to have somewhat similar profiles, but large differences were not

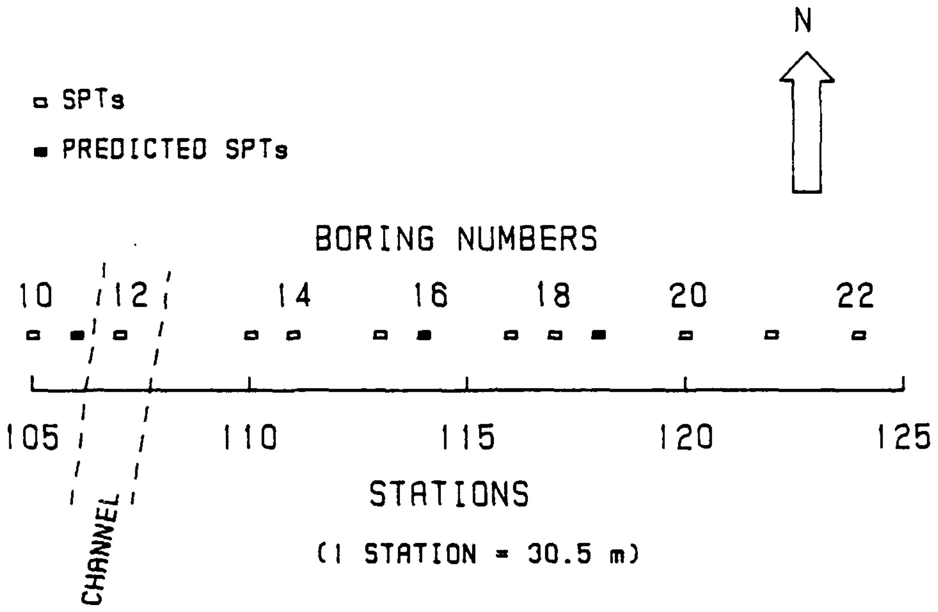


Figure 5-4. Spatial Variability Soundings at Apalachicola River

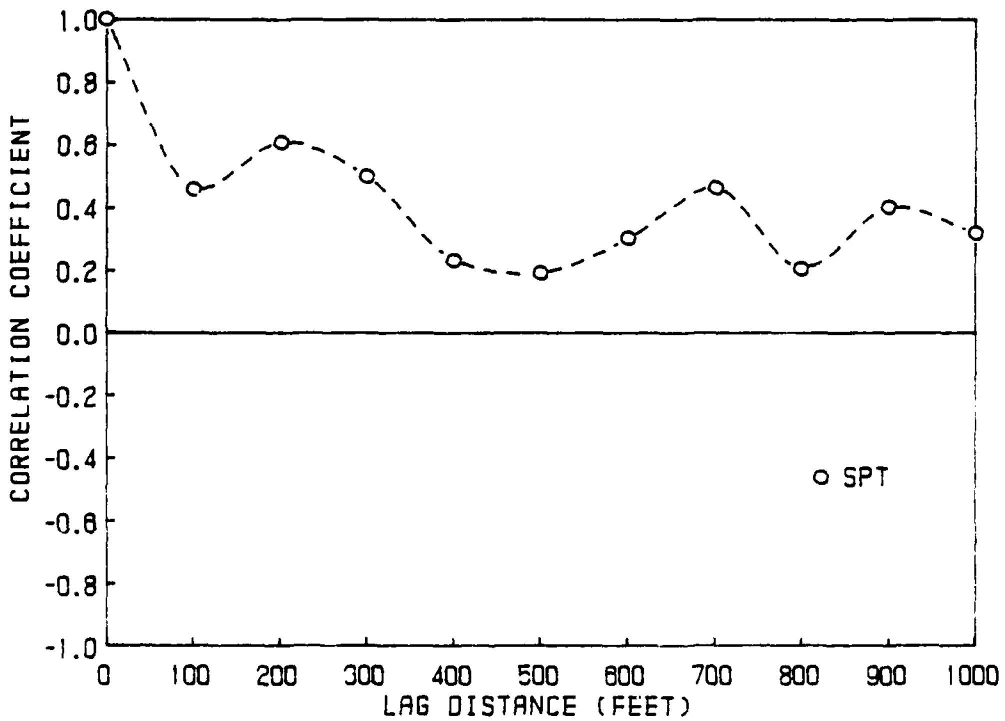


Figure 5-5. Autocorrelation Function for Normalized Raw Data at Apalachicola River

uncommon. Figure 5-5 shows the autocorrelation function for the raw SPT data. Note the generally decreasing correlation coefficient up to a lag distance of 500 feet (152 m). The correlation seems to improve slightly beyond 500 feet, but since autocorrelation functions are known to be less reliable at larger lag distances, this improvement is thought to be an artifact of the particular data set.

Archer Landfill. The final site evaluated for spatial variability was a future landfill located west of Archer, Florida. Ten electronic cone penetrometer soundings were used, spread out over approximately 0.7 hectares (1.7 acres). Figure 5-6 shows a plan view of the site. For this analysis, the data were located three-dimensionally since the soundings were not in a relatively straight line. Soundings #4, #5, and #8 were "predicted." The source of the data was a University of Florida Master's degree thesis by Basnett (7).

The spatial variability analysis was based on the ECPT soundings between elevations 20 and 30 meters (66-98 feet) (data were sparse below elevation 20 meters). The surface elevation averaged 31.85 meters MSL (104.5 ft MSL), with a range of 30.60 to 32.85 meters (100.4 to 107.8 ft). The soil is described as medium to fine-grained quartz sand. No water table was encountered.

The ECPT soundings show the site to have cone resistance and friction resistance values that generally increase with depth. The site is remarkably uniform, although measured stresses are somewhat more variable for the lower five meters (16 ft) of the sounding. Figure 5-7 shows the autocorrelation function for the raw SPT data. Autocorrelation was assumed to be a circular function in the horizontal plane. The uniformity of the site is reflected by the leveling off of

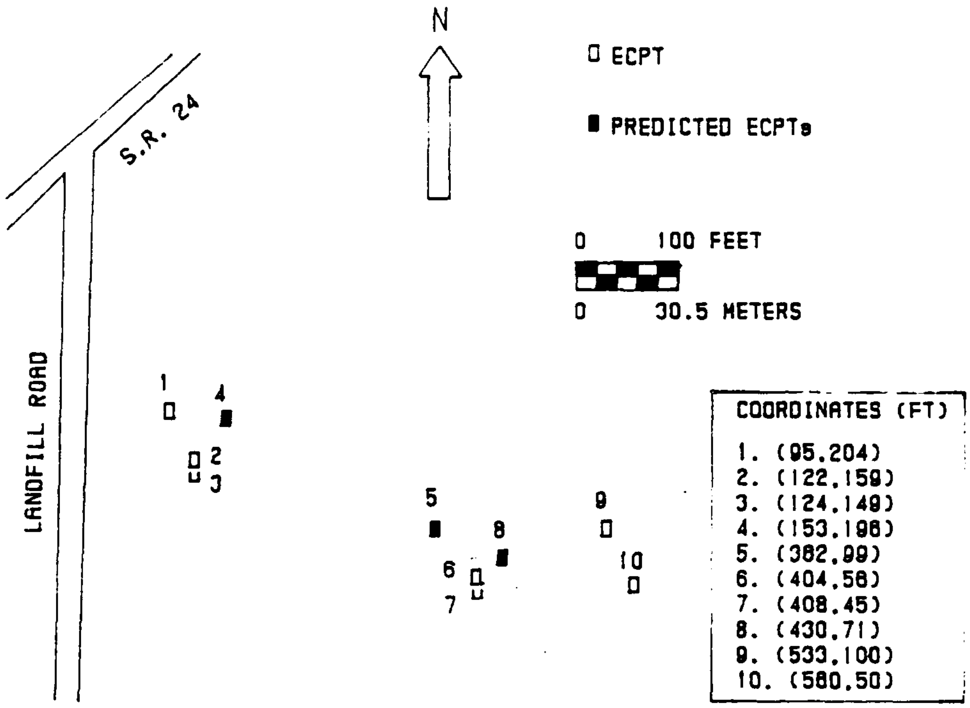


Figure 5-6. Spatial Variability Soundings at Archer Landfill

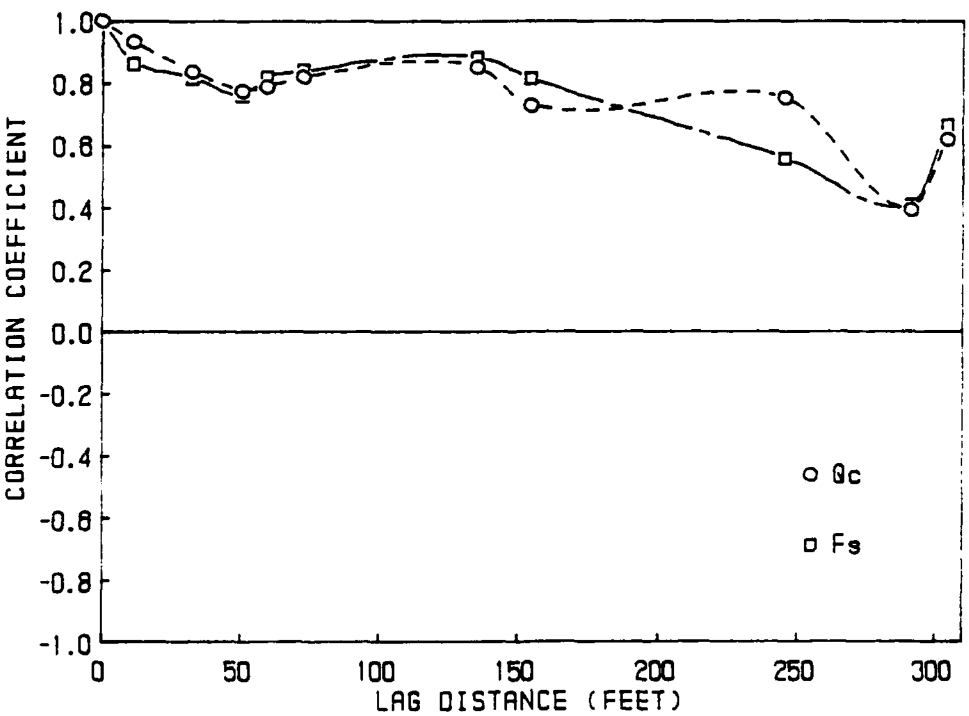


Figure 5-7. Autocorrelation Function for Normalized Raw Data at Archer Landfill

the correlation coefficients to values generally over 0.6 as far as 300 feet (91.4 m) apart.

Results and Discussion

Choctawhatchee Bay Site

Autocorrelation Function. Since the autocorrelation function for the normalized raw data did not level off to zero (Figure 5-3), a nonstationary component was assumed to be present. Following Kulatilake and Ghosh's recommended technique (26), a first order regression model (Model 1) was used to try to describe the trend. However, the autocorrelation function for the residuals from the regression analysis showed little change from Figure 5-3. Again increasing the order of the regression model one step (Model 2), the autocorrelation function began to approach the expected leveling-off behavior. In order to better describe the trend component, the STEPWISE model generator in the SAS system was employed. A four-term model was selected for both q_c and f_s:

$$q_c = b_0 + b_1D + b_2D^2 + b_3D^8 + b_4D^5X \qquad R^2 = 0.55 \quad \ldots\ldots\ldots\ldots\ldots (5\text{-}8)$$

$$f_s = b_0 + b_1D^2 + b_2X^2 + b_3DX + b_4D^5X \qquad R^2 = 0.65 \quad \ldots\ldots\ldots\ldots\ldots (5\text{-}9)$$

in which D is the depth in meters, and X is the distance from Sounding A in feet. This model produced the autocorrelation functions used in the analysis (Figure 5-8):

By trial and error an exponential curve corresponding to equation 5-2 was fitted to both the cone resistance and friction resistance data of Figure 5-8 (since the two curves were very similar). A constant (β) of 20, and a range of 50 feet were estimated. The fact that the range

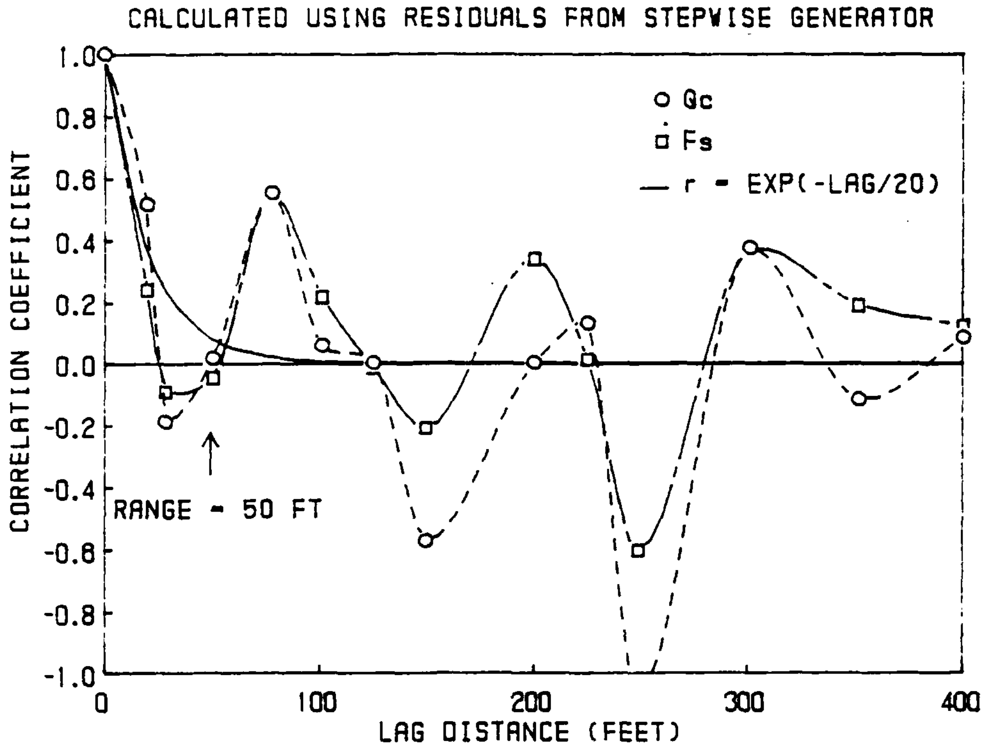


Figure 5-8. Final Autocorrelation Function for Choctawhatchee Bay

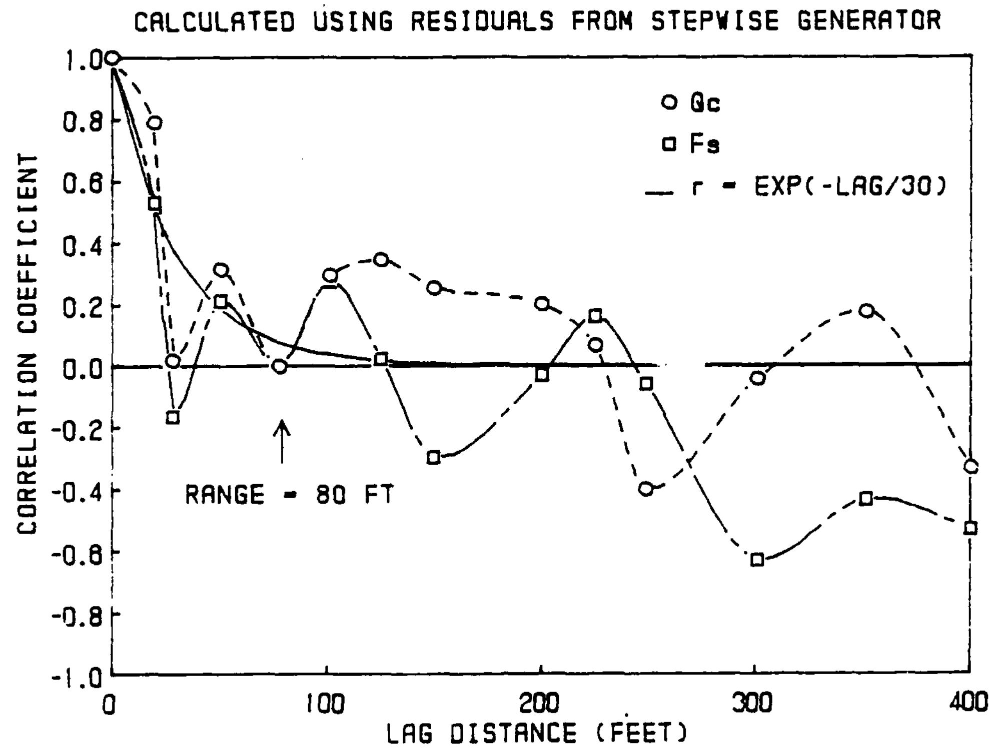


Figure 5-9. Final Autocorrelation Function for Choctawhatchee Bay Using Transformed Data Set

is relatively small at a site that is considered well-correlated suggests that the regression model may do a good job of describing the site by itself. A result of the small range, however, is that there are no soundings within 50 feet of Sounding H. Therefore, the weight methods and the random field models were not applied to this sounding.

In similar fashion the autocorrelation functions for the transformed variables were also determined. In this instance, a Model 2 regression was sufficient to remove the nonstationary portion of the friction data, whereas the STEPWISE model generator was required for the cone resistance data. The generated model was identical to Equation 5-8 above, except that D^7 was used instead of D^8 (R^2 = 0.53). For both the q_c and f_s autocorrelation functions, a β of 30 and a range of 80 feet were estimated (Figure 5-9), which is (predictably) very similar to the functions estimated using the nontransformed variables.

Estimation models. Table 5-1 compares the parameters used for the deterministic models, along with the parameters' standard deviations. Note that the standard deviation for the median was estimated using equations 4-5 and 4-6, and assuming the cone resistance and friction resistance values are normally distributed. While this assumption is not generally true (as was seen in Figure 5-1 which compared transformed and nontransformed frequency distributions), such an assumption permits comparison with the mean and the trimmed average standard deviation estimates, which also assume normality. Also note that a range encompassing approximately 68% of the data ($\pm$ one standard deviation) is given for the logarithmic variables, since the transformation tends to skew the variable values and prohibits describing the "de-transformed" standard deviation with a single number. The effect of the large outlier values for q_c and f_s can be seen in Table 5-1. The parameter and standard deviation estimates using the mean (which accounts for all values of the variable) is larger than for any of the other methods (which in various ways tend to minimize the effects of extreme values).

Table 5-1. Deterministic Model Parameters for Choctawhatchee Bay Site

Deterministic Model Type	Cone Resistance (MPa) Estimate	Cone Resistance (MPa) Std Dev	Friction Resistance (kPa) Estimate	Friction Resistance (kPa) Std Dev
Mean	5.89	6.04	22.3	29.8
Log Mean	3.33	1.11-10.01	8.6	2.0-38.1
Median	4.03	4.52	12.6	16.6
Log Median	3.93	1.17-13.18	11.2	1.7-74.5
Trimmed Average	4.72	3.33	15.9	15.0
Log Trimmed Average	3.36	1.47-7.66	8.4	2.5-28.3

Tables 5-2 and 5-3 summarize the regression analyses, including their squared multiple correlation coefficients (R^2), and the root mean square errors (RMSE) for the regressions over the whole site (less the sounding to be predicted). Appendix F summarizes the steps in the STEPWISE procedure as well as the variables selected for the low term and high term regression models.

Prediction results. Tables 5-4 and 5-5 summarize the root mean square errors obtained by applying the various estimation models to predict the three target soundings. Figures 5-10 and 5-11 graphically summarize the information contained in Tables 5-4 and 5-5, respectively.

A study of Figures 5-10 and 5-11 show several items of interest. The three single-value methods (mean, median and trimmed average) all give approximately the same level of error. This level of error was generally improved on in estimating the friction values using the more "sophisticated" methods, but such improvement was less reliable in

Table 5-2. Regression Models for the Prediction of Cone Resistance at the Choctawhatchee Bay Site

Sounding	Model Type	R^2	RMSE
E	Model 1	0.11	5.81
	Model 2	0.42	4.67
	Low Term	0.46	4.54
	High Term	0.54	4.19
	Model 1 (Log)	0.05	0.46
	Model 2 (Log)	0.41	0.36
	Low Term (Log)	0.53	0.32
	High Term (Log)	0.55	0.32
H	Model 1	0.11	5.85
	Model 2	0.45	4.61
	Low Term	0.58	4.05
	High Term	0.61	3.90
	Model 1 (Log)	0.05	0.47
	Model 2 (Log)	0.44	0.36
	Low Term (Log)	0.57	0.32
	High Term (Log)	0.66	0.29
J	Model 1	0.08	5.75
	Model 2	0.40	4.66
	Low Term	0.42	4.58
	High Term	0.50	4.24
	Model 1 (Log)	0.03	0.47
	Model 2 (Log)	0.40	0.37
	Low Term (Log)	0.51	0.34
	High Term (Log)	0.53	0.33

Note: The RMSE for the logarithmic approach was left in its transformed state to preserve its true value and meaning.

Table 5-3. Regression Models for the Prediction of Friction Resistance at the Choctawhatchee Bay Site

Sounding	Model Type	R^2	RMSE
E	Model 1	0.25	26.2
	Model 2	0.52	21.1
	Low Term	0.63	18.5
	High Term	0.67	17.6
	Model 1 (Log)	0.17	0.58
	Model 2 (Log)	0.40	0.49
	Low Term (Log)	0.48	0.46
	High Term (Log)	0.52	0.44
H	Model 1	0.24	26.8
	Model 2	0.53	21.1
	Low Term	0.64	18.4
	High Term	0.68	17.5
	Model 1 (Log)	0.14	0.62
	Model 2 (Log)	0.41	0.51
	Low Term (Log)	0.48	0.48
	High Term (Log)	0.54	0.46
J	Model 1	0.23	26.2
	Model 2	0.51	20.9
	Low Term	0.65	17.7
	High Term	0.66	17.4
	Model 1 (Log)	0.13	0.59
	Model 2 (Log)	0.39	0.50
	Low Term (Log)	0.47	0.47
	High Term (Log)	0.52	0.44

Note: The RMSE for the logarithmic approach was left in its transformed state to preserve its true value and meaning.

Table 5-4. Results of q_c Analysis at Choctawhatchee Bay

ROOT MEAN SQUARE ERROR (MPa)

METHOD	QE	QH	QJ	LOG QE	LOG QH	LOG QJ
MEAN	4.89	3.75	6.59	4.85	3.28	7.19
MEDIAN	4.81	3.31	7.27	4.73	3.21	6.88
TRIMMED AVG	4.76	3.36	6.97	4.84	3.27	7.17
WEIGHT (a/d)	6.54		3.02	5.30		3.17
WEIGHT (a/d2)	6.46		3.17	5.71		3.30
REG MODEL 1	5.22	4.74	5.93	4.91	3.42	6.66
REG MODEL 2	3.44	4.38	3.61	3.47	3.78	4.28
REG LO TERM	3.75	5.12	3.07	3.59	5.25	2.97
REG HI TERM	3.48	5.34	2.70	3.57	2.91	3.58
RANDOM FIELD	6.33		3.08	4.80		2.77
LINEAR INTERP	6.32	6.64	2.92	5.95	6.22	2.73

NOTE: QE = q_c at Station 114+78
QH = q_c at Station 117+00
QJ = q_c at Station 119+00

Table 5-5. Results of f_s Analysis at Choctawhatchee Bay

ROOT MEAN SQUARE ERROR (kPa)

METHOD	FE	FH	FJ	LOG FE	LOG FH	LOG FJ
MEAN	23.6	17.8	30.1	26.1	19.0	31.0
MEDIAN	23.8	17.2	30.6	25.8	18.6	30.7
TRIMMED AVG	23.3	16.8	30.1	26.1	19.0	31.0
WEIGHT (a/d)	24.0		25.6	18.2		24.8
WEIGHT (a/d2)	23.7		25.7	20.2		25.0
REG MODEL 1	24.9	17.5	25.5	21.1	13.5	24.7
REG MODEL 2	16.6	15.6	18.7	16.0	10.5	14.9
REG LO TERM	15.8	14.9	18.9	17.8	13.0	19.1
REG HI TERM	16.5	16.8	18.1	17.4	16.4	13.3
RANDOM FIELD	23.4		24.9	16.3		24.6
LINEAR INTERP	23.2	20.7	21.1	21.5	19.9	17.9

NOTE: FE = f_s at Station 114+78
FH = f_s at Station 117+00
FJ = f_s at Station 119+00

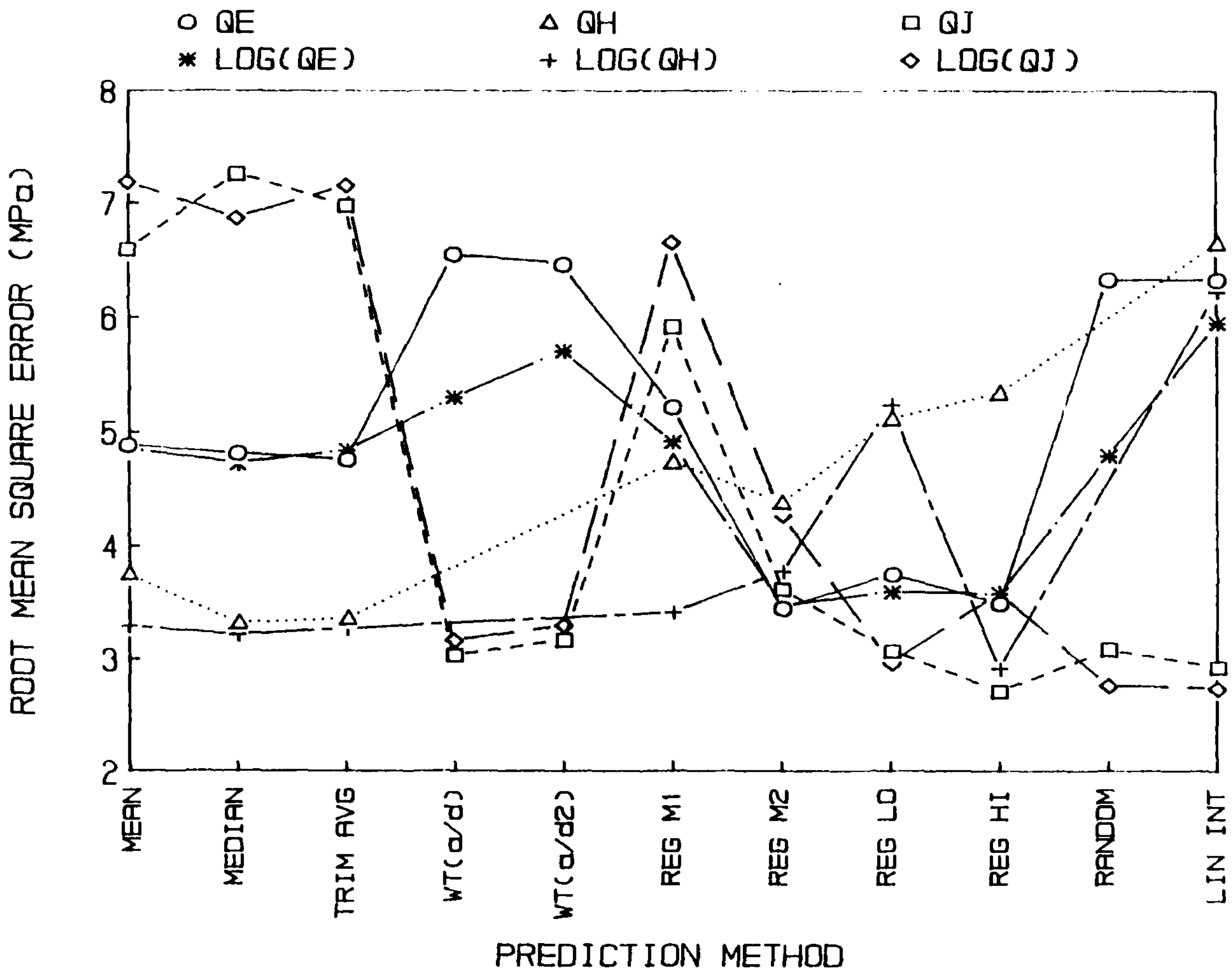


Figure 5-10. Prediction RMSEs for Cone Resistance at Choctawhatchee Bay

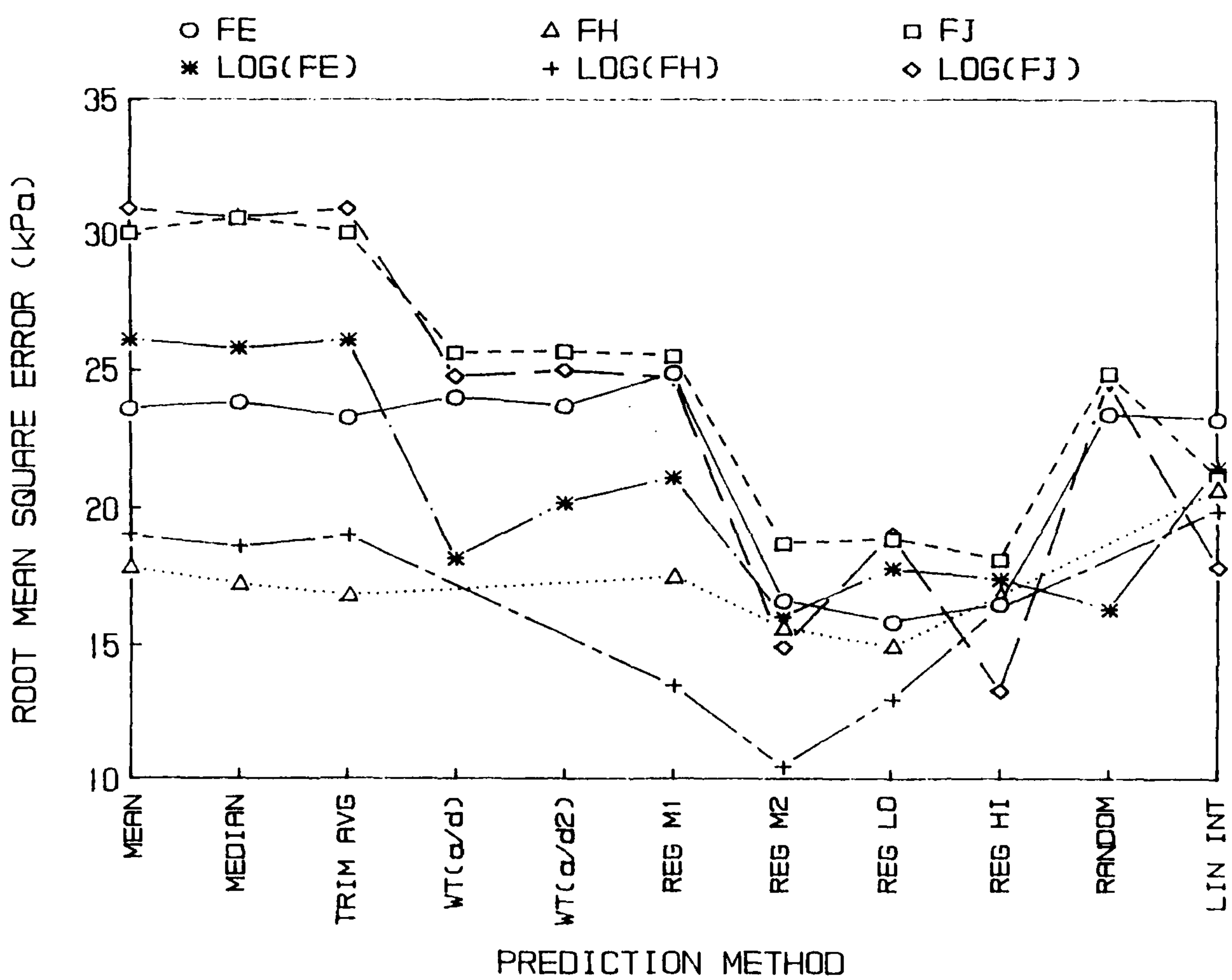


Figure 5-11. Prediction RMSEs for Friction Resistance at Choctawhatchee Bay

estimating cone resistance. Note also the usually small differences between the various distance-weighting methods (the two weight methods, the random field model, and the linear interpolation method). Apparently no method of assigning weights is consistently superior.

Of particular interest is the performance of the higher order regression models (Model 2, Low Term and High Term). These models were the most consistent estimators, producing relatively good RMSE's with less scatter than the other methods evaluated. The range of approximately 3-5 MPa for the q_c RMSE compares well with the expected RMSE's of approximately 4-5 MPa from Table 5-2. Similarly, the f_s range of 15-19 kPa compares well with Table 5-3's range of approximately 17-21 kPa.

Table 5-6, which is based on the data in Tables 5-4 and 5-5, is useful for evaluating the effects of using the logarithmic transformation on the data. In this table, positive values indicate a higher error using the nontransformed data set, whereas negative values indicate the opposite. While the nontransformed single-value estimates seem to be superior, on average the logarithmic transformation appears to improve (albeit slightly) the predictions.

Despite the appeal of a single number (the RMSE) to evaluate and compare the various prediction methods, an inspection of plots of the actual predictions is necessary to completely compare one method against another. Figures 5-12 through 5-14 show some typical prediction plots using several of the estimation models.

Figure 5-12 shows the weighting prediction (using a/d) for f_s at Sounding J. This plot is virtually indistinguishable from any of the other weighting or interpolation methods (whether employing transformed

Table 5-6. Comparison of Transformed and Nontransformed Approaches at Choctawhatchee Bay

RMSE(REGULAR) - RMSE(LOG)

(a) CONE RESISTANCE (MPa)

METHOD	QE	QH	QJ	Q AVG
MEAN	0.04	0.48	-0.60	-0.03
MEDIAN	0.08	0.09	0.39	0.19
TRIMMED AVG	-0.08	0.09	-0.20	-0.07
WEIGHT (a/d)	1.24		-0.15	0.55
WEIGHT (a/d2)	0.75		-0.13	0.31
REG MODEL 1	0.31	1.31	-0.73	0.30
REG MODEL 2	-0.03	0.60	-0.67	-0.04
REG LO TERM	0.15	-0.13	0.10	0.04
REG HI TERM	-0.09	2.43	-0.88	0.49
RANDOM FIELD	1.53		0.31	0.92
LINEAR INTERP	0.38	0.42	0.19	0.33

(b) FRICTION RESISTANCE (kPa)

METHOD	FE	FH	FJ	F AVG
MEAN	-2.4	-1.2	-0.9	-1.5
MEDIAN	-2.0	-1.4	-0.1	-1.2
TRIMMED AVG	-2.7	-2.2	-0.9	-1.9
WEIGHT (a/d)	5.8		0.8	3.3
WEIGHT (a/d2)	3.6		0.7	2.1
REG MODEL 1	3.8	4.0	0.8	2.9
REG MODEL 2	0.5	5.1	3.7	3.1
REG LO TERM	-2.1	1.9	-0.2	-0.1
REG HI TERM	-0.9	0.4	4.8	1.4
RANDOM FIELD	7.1		0.3	3.7
LINEAR INTERP	1.8	0.8	3.2	1.9

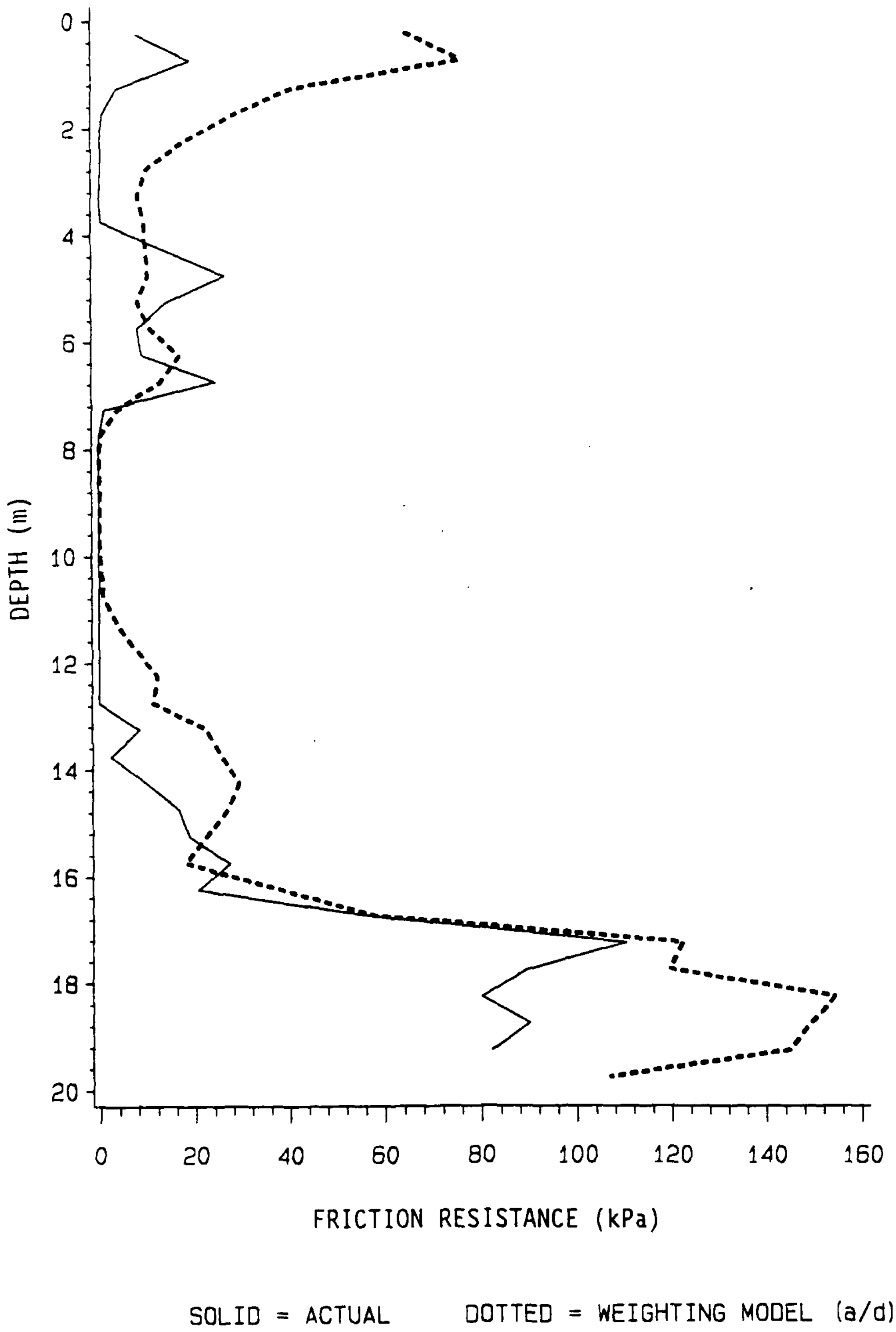


Figure 5-12. Prediction of f_s for Sounding J Using a Weighting Model (a/d) at Choctawhatchee Bay

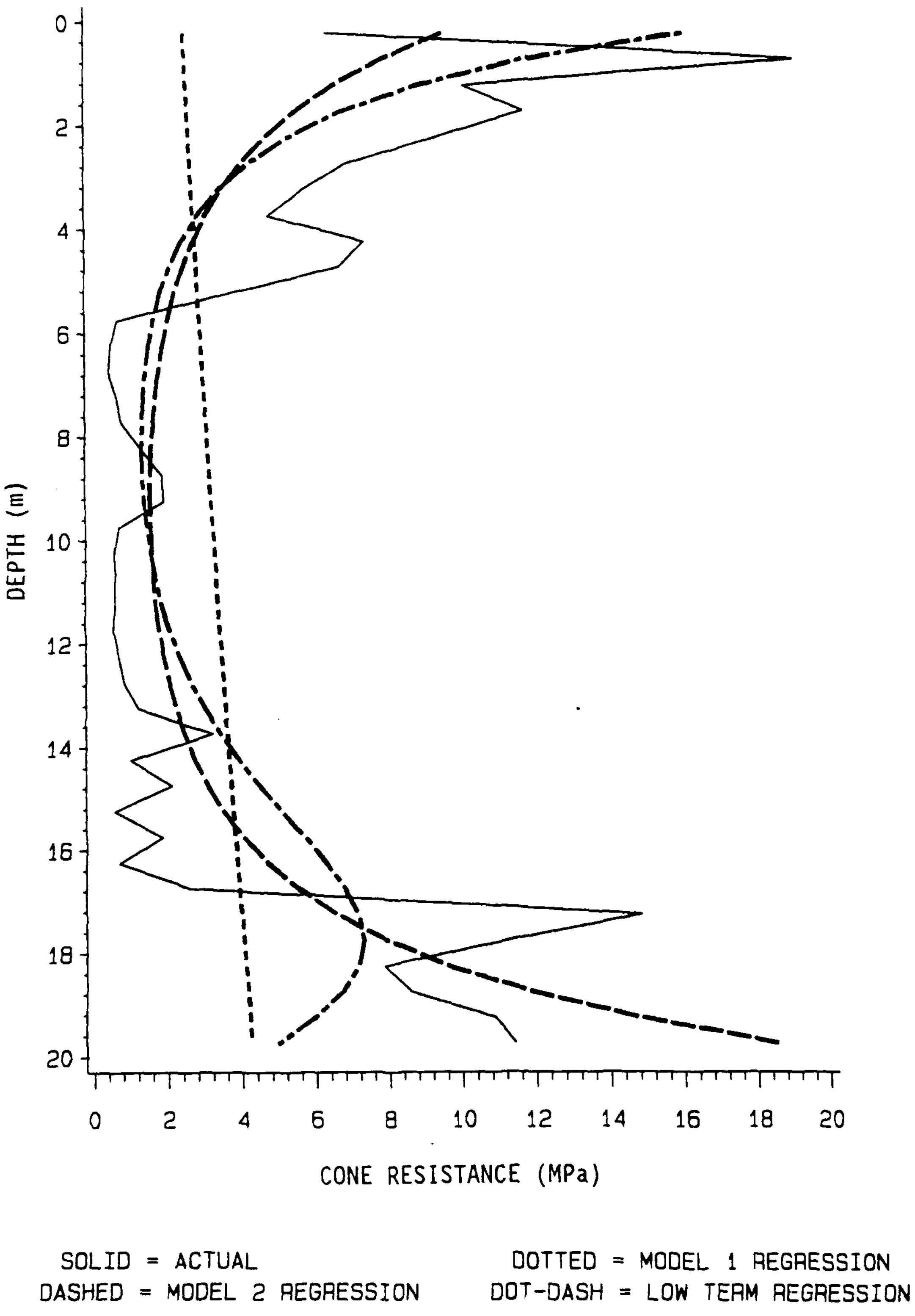
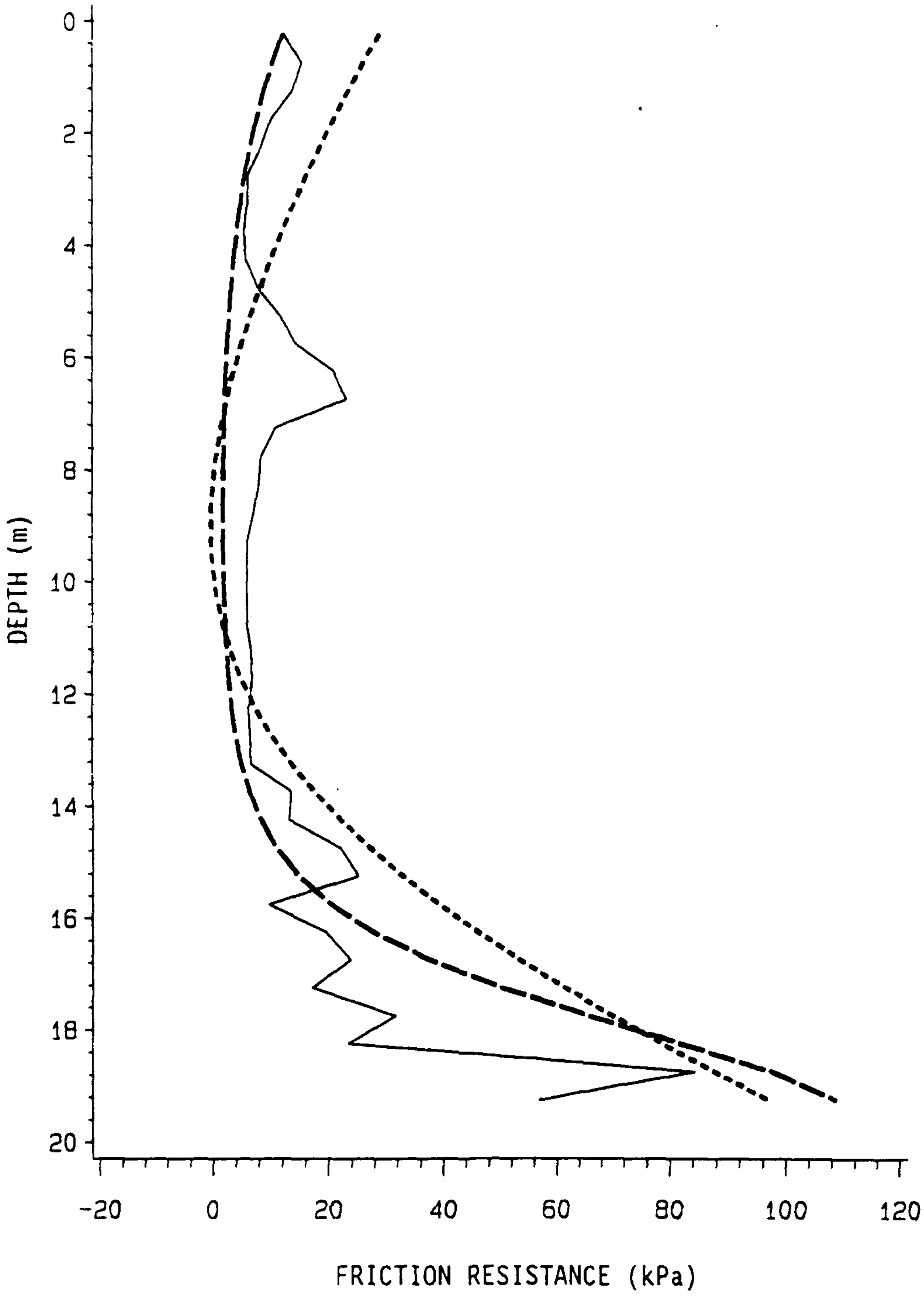


Figure 5-13. Prediction of q_c for Sounding E Using Various Regression Models at Choctawhatchee Bay



SOLID = ACTUAL DOTTED = HIGH TERM REGRESSION (REGULAR)
DASHED = HIGH TERM REGRESSION (LOG TRANSFORMATION)

Figure 5-14. Prediction of f_s for Sounding H Using High Term Regression with Transformed and Regular Data at Choctawhatchee Bay variables or not), including the random field model. As was noted for most of the distance-weighting predictions, a large proportion of the error in the prediction occurred near the bottom of the sounding where the more variable, higher-strength soil layer was encountered.

Figure 5-13 compares three typical regression model predictions: Model 1, Model 2 and Low Term Model. The selected example is cone resistance at Sounding E using the transformed data. As was suggested by the RMSE's presented in Tables 5-4 and 5-5, the Model 1 regression does the poorest job of predicting the sounding, but once enough higher order terms are introduced the differences in the various regression models are minor.

The effect of the logarithmic transformation can be seen in Figure 5-14. The transformed prediction is somewhat preferential towards the lower magnitude values, making it usually more conservative in its strength predictions. Note that one of the problems with using non-logarithmic variables in regression is demonstrated in the figure. At approximately 9 meters depth the prediction is slightly negative, which is physically impossible. Using a logarithmic transformation would avoid such an estimate.

Apalachicola River Site

Autocorrelation function. Figures 5-15 and 5-16 show the fitted autocorrelation function for the SPT N values and log(N) values, respectively. In both cases, a Model 2 regression was used to remove the nonstationary component of the data set. As a result of the transformation, somewhat different autocorrelation functions were obtained. For the non-transformed N values the β constant was 125 and

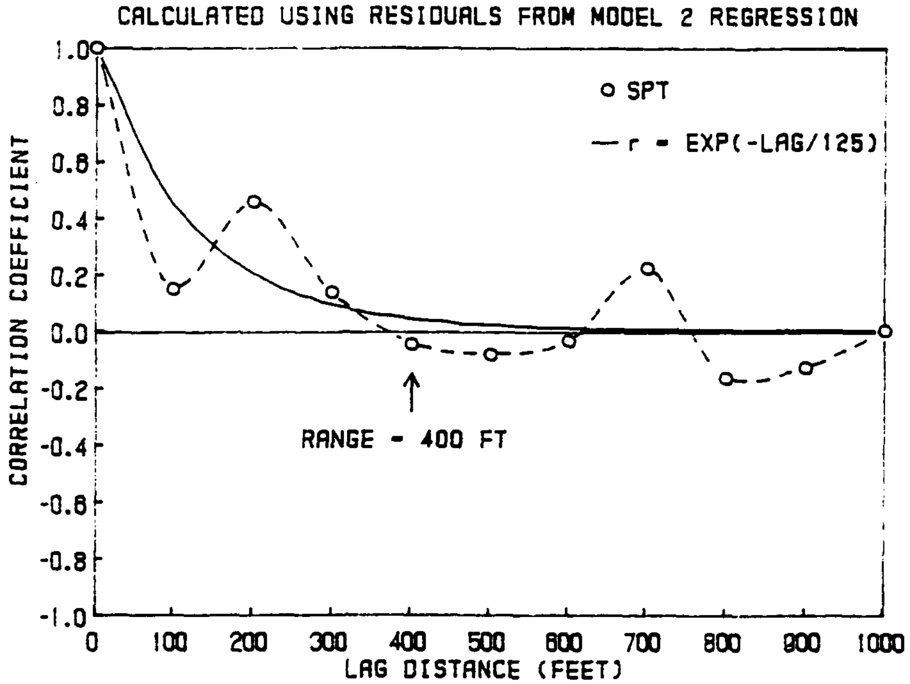


Figure 5-15. Final Autocorrelation Function for Apalachicola River

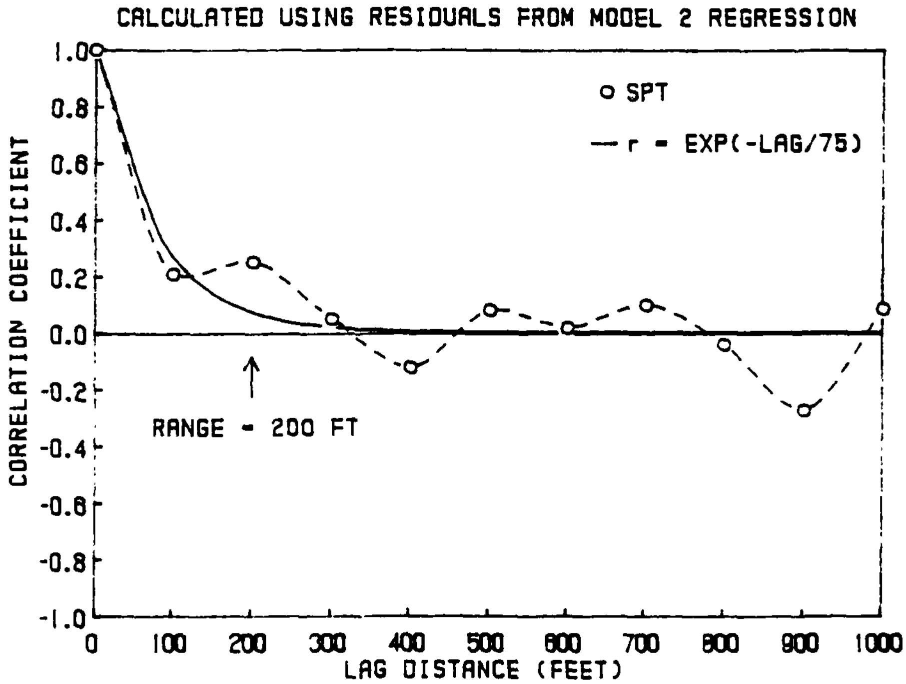


Figure 5-16. Final Autocorrelation Function for Apalachicola River Using Transformed Data Set

the range was 400 feet; for the log(N) values the constant was 75 and the range was 200 feet.

Fitting the exponential curve is very subjective, and arguments could easily be made for curves different from those selected. Note in Figures 5-15 and 5-16 that the exponential curve fitted to the regular data is a good "average" curve, whereas the curve fitted to the logarithmic data favors the first major data point (which is at a 100 foot distance).

Estimation models. Table 5-7 compares the deterministic model parameters at Apalachicola in the same manner as Table 5-1 did for Choctawhatchee Bay. Table 5-8 summarizes the regression analyses, including their squared multiple correlation coefficients (R^2), and the root mean square errors (RMSE) for the regressions over the whole site (less the sounding to be predicted). Appendix F summarizes the steps in the STEPWISE procedure as well as the variables selected for the low term and high term regression models.

Prediction results. Table 5-9 summarizes the root mean square errors obtained by applying the various estimation models to predict the three target soundings. This information is graphically presented in Figure 5-17.

Table 5-7. Deterministic Model Parameters for Apalachicola River Site

	SPT N-Value (blows/ft)	
Model Type	Estimate	Std Dev
Mean	25.2	31.4
Log(Mean)	12.3	3.4-44.6
Median	14.0	16.4
Log(Median)	14.0	4.2-46.7
Trimmed Average	19.0	14.8
Log(Trimmed Average)	14.2	6.5-31.2

Table 5-8. Regression Models for the Prediction of the SPT N-Value at the Apalachicola River Site

Station	Model Type	R^2	RMSE
106+00	Model 1	0.21	27.7
(#11)	Model 2	0.29	26.2
	Low Term	0.33	25.4
	High Term	0.37	24.8
	Model 1 (Log)	0.51	0.39
	Model 2 (Log)	0.69	0.31
	Low Term (Log)	0.71	0.30
	High Term (Log)	0.74	0.29
114+00	Model 1	0.22	25.9
(#16)	Model 2	0.30	24.6
	Low Term	0.34	24.0
	High Term	0.38	23.3
	Model 1 (Log)	0.52	0.38
	Model 2 (Log)	0.69	0.30
	Low Term (Log)	0.65	0.32
	High Term (Log)	0.71	0.29
118+00	Model 1	0.23	28.8
(#19)	Model 2	0.32	27.2
	Low Term	0.34	26.7
	High Term	0.39	25.7
	Model 1 (Log)	0.54	0.39
	Model 2 (Log)	0.72	0.31
	Low Term (Log)	0.75	0.29
	High Term (Log)	0.77	0.28

Note: The RMSE for the logarithmic approach was left in its transformed state to preserve its true value and meaning.

Table 5-9. Results of Spatial Variability Study at Apalachicola River

ROOT MEAN SQUARE ERROR (BLOWS/FT)

METHOD	#11	#16	#19	LOG #11	LOG #16	LOG #19
MEAN	37.8	53.0	13.7	44.7	59.4	7.9
MEDIAN	43.6	58.4	7.8	43.6	58.4	7.8
TRIMMED AVG	40.7	55.8	9.3	52.5	66.4	14.9
WEIGHT (a/d)	44.8	33.1	24.0	47.8	23.6	20.5
WEIGHT (a/d2)	46.6	30.9	22.6	47.8	26.8	6.3
REG MODEL 1	31.6	48.9	17.6	38.1	55.6	19.0
REG MODEL 2	28.4	45.1	16.7	32.6	49.9	11.1
REG LO TERM	31.4	45.5	15.5	34.4	49.5	13.0
REG HI TERM	29.5	43.3	18.3	33.8	47.2	12.7
RANDOM FIELD	46.3	29.5	23.7	47.7	26.2	19.6
LINEAR INTERP	49.1	22.0	16.9	49.6	20.6	15.8

NOTE: #11 = N at Station 106+00, BLOWS/FT (Boring #11)
#16 = N at Station 114+00, BLOWS/FT (Boring #16)
#19 = N at Station 118+00, BLOWS/FT (Boring #19)

Table 5-9 and Figure 5-17 suggest that predicting SPT blow counts at the Apalachicola River site is nearly impossible to any reasonable degree of accuracy. Even the best sounding (#19) had an average error of approximately 15 blows/ft. The average RMSE from the regression analyses of approximately 26 blows/ft would be nonconservative for two of the soundings. Part of the problem likely lies with the SPT test itself. Bowles cites the work of several researchers which are critical of the reproducibility of the Standard Penetration Test (8), raising the question whether or not the term "test" really applies. In any case, the site appears to show significant spatial variability, making any prediction difficult.

No single method of prediction stood out at the Apalachicola River site. The methods which employed a weight based on separation distance (weight methods, random field method, and linear interpolation) made a

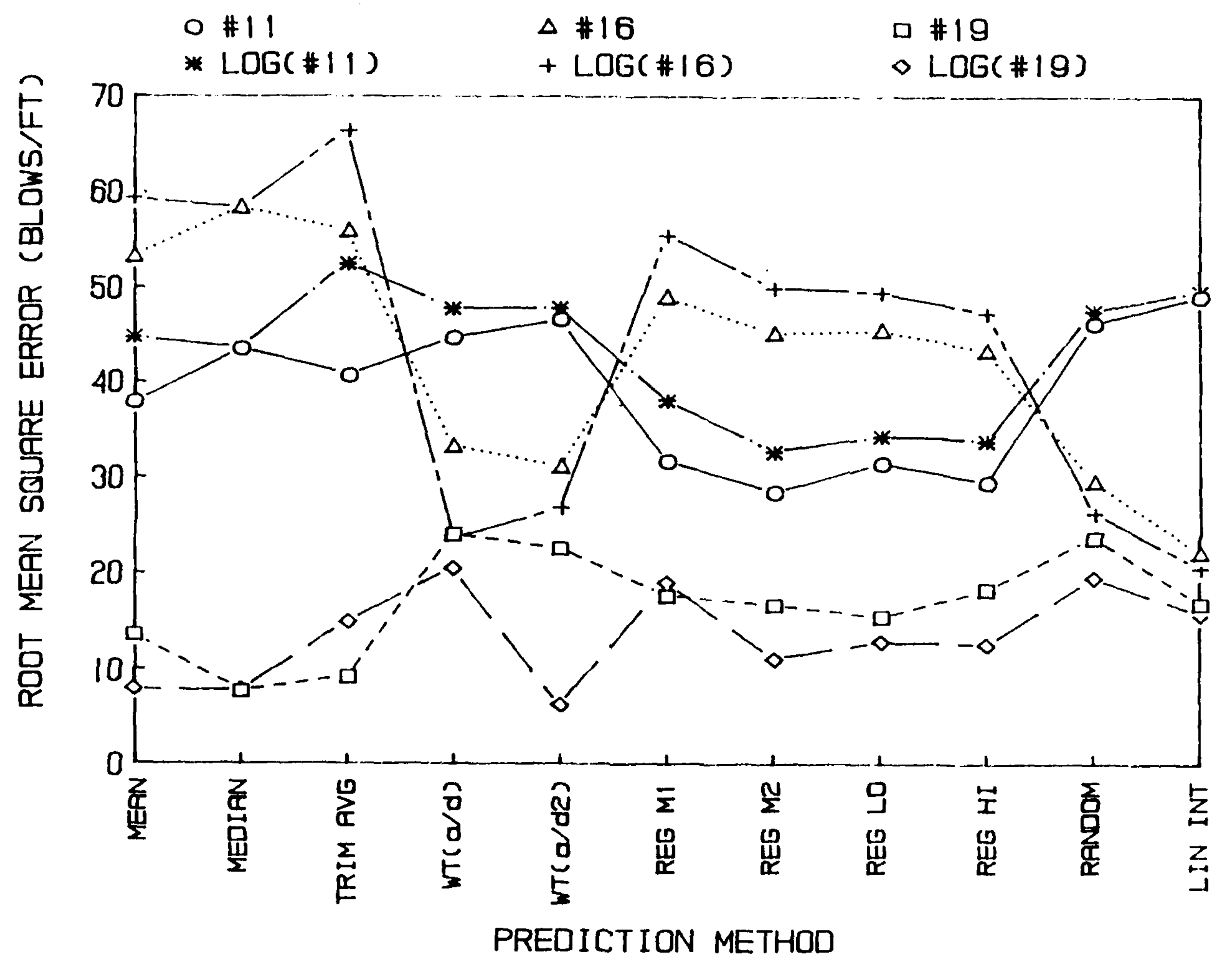


Figure 5-17. Prediction RMSEs for SPT N-Values at Apalachicola River

significant improvement in the prediction for Boring #16, whereas the regression models did the best job for Boring #11. No single method stood out for Boring #19--all methods did a comparatively good job of predicting the sounding.

Table 5-10 can be used to evaluate the effects of using the logarithmic transformation on the SPT data. While the differences are generally modest, the logarithmic transformation appears to usually be beneficial for the distance-weighting approaches, and detrimental to the single-value and regression approaches.

Table 5-10. Comparison of Transformed and Nontransformed Approaches at Apalachicola River

RMSE(REGULAR) - RMSE(LOG)

SPT N VALUES (BLOWS/FT)

METHOD	#11	#16	#19	AVG
MEAN	-6.9	-6.3	5.7	-2.5
MEDIAN	0.0	0.0	0.0	0.0
TRIMMED AVG	-11.8	-10.6	-5.6	-9.3
WEIGHT (a/d)	-3.0	9.6	3.5	3.4
WEIGHT (a/d2)	-1.2	4.1	16.3	6.4
REG MODEL 1	-6.5	-6.7	-1.4	-4.9
REG MODEL 2	-4.3	-4.9	5.6	-1.2
REG LO TERM	-2.9	-4.0	2.5	-1.5
REG HI TERM	-4.4	-3.9	5.5	-0.9
RANDOM FIELD	-1.4	3.3	4.0	2.0
LINEAR INTERP	-0.5	1.4	1.1	0.6

To complete the evaluation of the various prediction methods at the Apalachicola River site, an inspection of plots of the actual predictions was made. Typical results are presented in Figures 5-18 and 5-19.

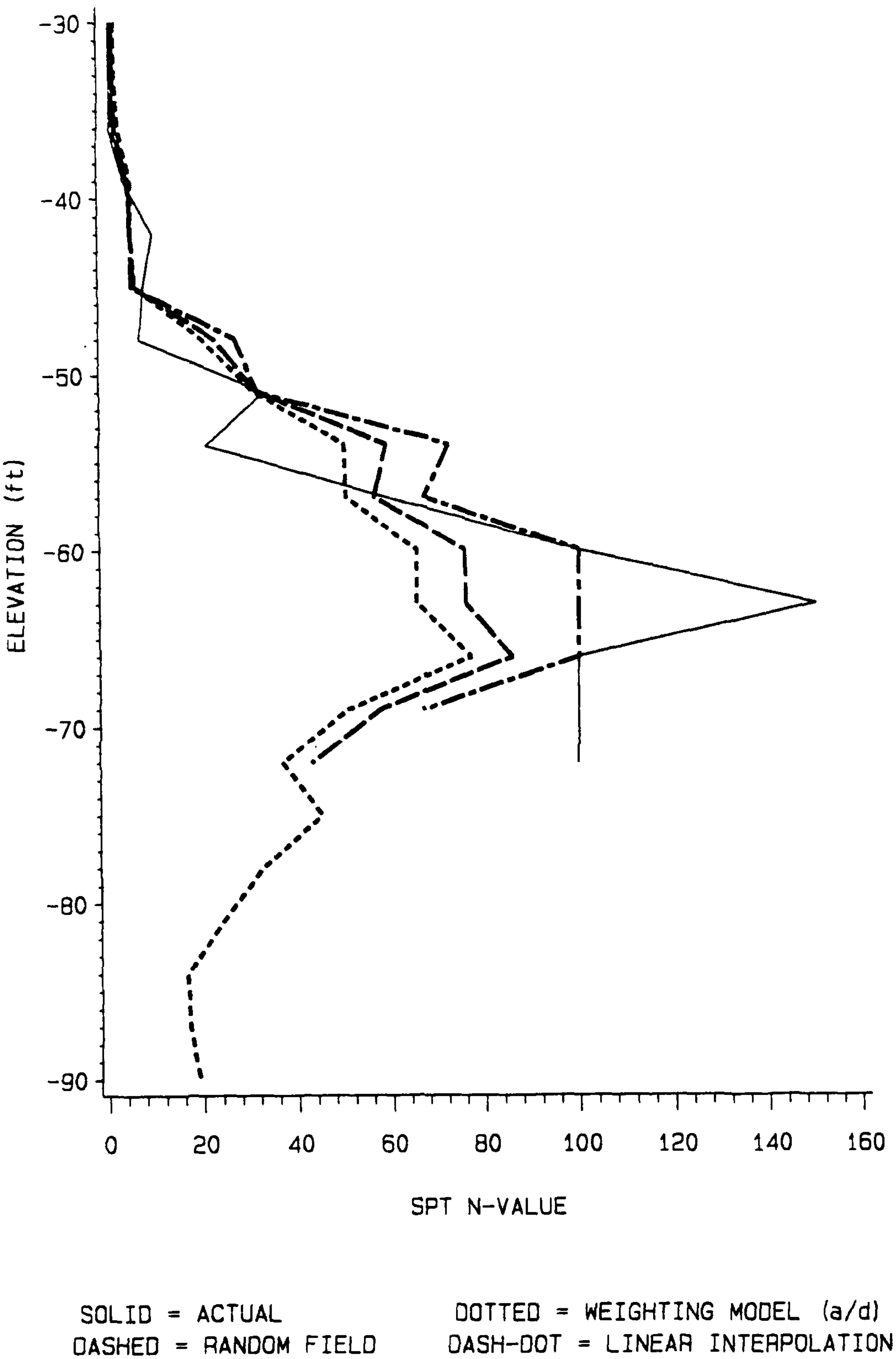


Figure 5-18. Prediction of N for Sounding #16 Using Various Distance-Weighting Models at Apalachicola River

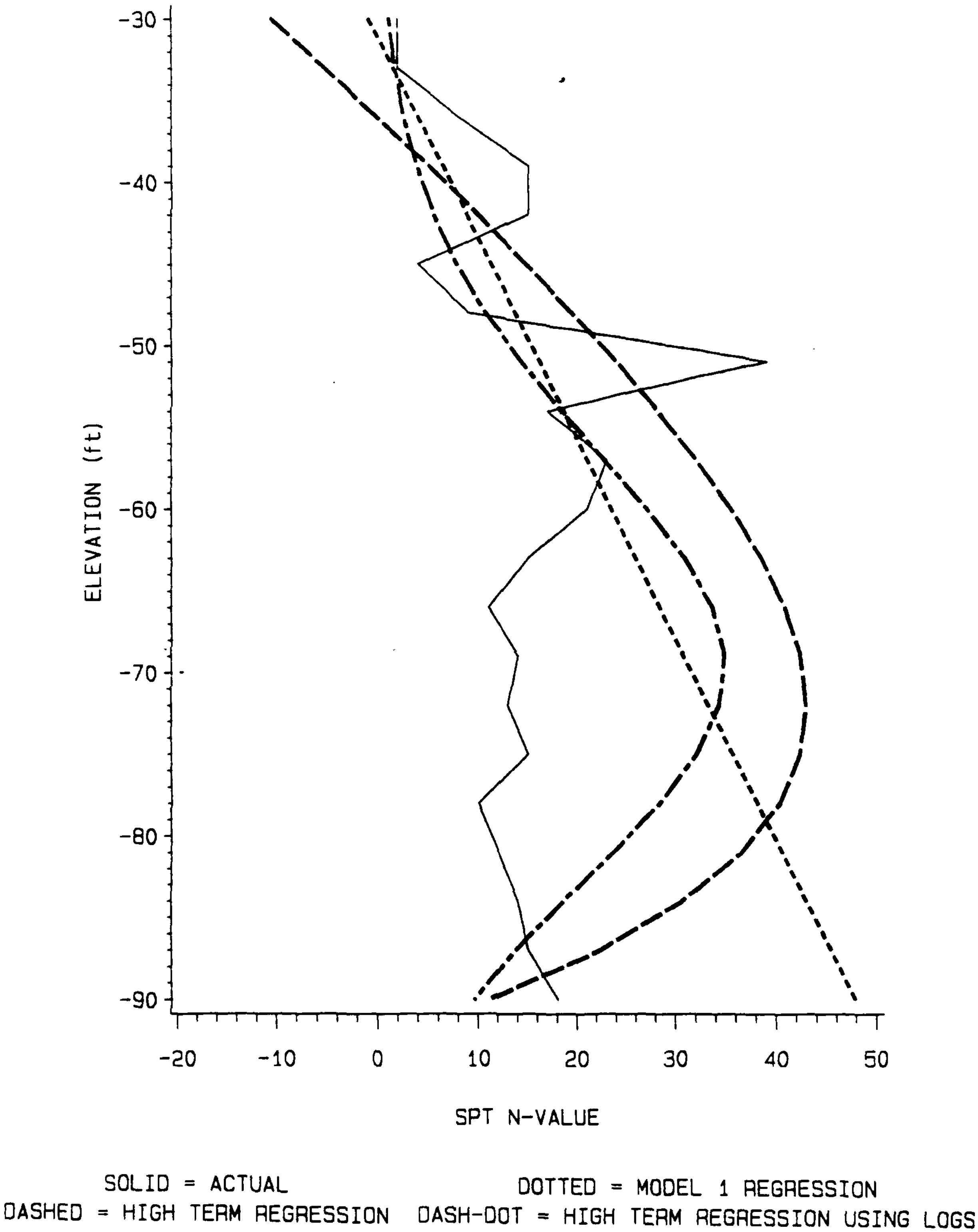


Figure 5-19. Prediction of N for Sounding #19 Using Various Regression Models at Apalachicola River

Figure 5-18 compares several of the distance-weighting approaches for Boring #16. At the Apalachicola River site the large variation in the SPT N values, especially below elevation -50 feet, resulted in some differences among the various methods. Depending on the number of soundings used to make the prediction and their relative weights, fairly significant differences in the predictions were obtained. Nevertheless, no one method seemed to consistently outperform the others.

Figure 5-19 compares several of the regression models for Boring #19. None of the regression models describe the sounding well, despite relatively low RMSE's for this boring. Note also that the high term regression model predicts negative values near the surface, and is generally less conservative than its transformed counterpart.

As a result of the spatial variability study at the Apalachicola River site, one can conclude that prediction between soundings is not possible to any reasonable degree of accuracy. As a result, soundings at (or very near) the locations of interest will be needed for design purposes.

Archer Landfill Site

As a result of the generally favorable (albeit small) effects of using the logarithmic transformation on data at the Choctawhatchee Bay and Apalachicola River sites, only a transformed data set was analyzed at the Archer Landfill site.

Autocorrelation Function. Figure 5-20 shows the fitted autocorrelation functions for the CPT q_c and f_s values at the Archer Landfill. A Model 1 regression was used to remove the nonstationary component of the data set. Slightly different autocorrelation functions

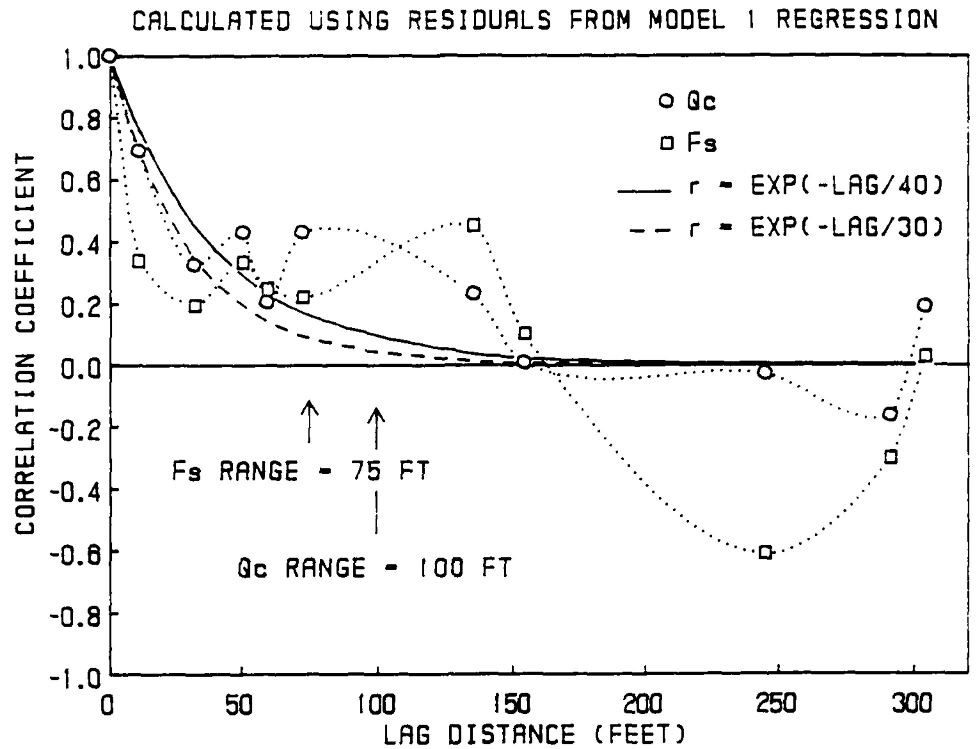


Figure 5-20. Final Autocorrelation Function for Archer Landfill Using Transformed Data Set

were obtained for the two measurements. For the cone resistance measurements, the constant was 40 and the range was 100 feet. For the friction resistance, the constant was 30 and the range was 75 feet.

<u>Estimation Models</u>. Table 5-11 compares the parameters used for the deterministic models at the Archer Landfill. Tables 5-12 and 5-13 summarize the regression analyses for each site predicted. Appendix F summarizes the steps in the STEPWISE procedure along with the variables selected for the low term and high term regression models.

<u>Prediction results</u>. Table 5-14 summarizes the root mean square errors obtained by applying the various estimation models to predict the three target soundings. Figures 5-21 and 5-22 graphically summarize the information contained in Table 5-14.

As was noted at the Choctawhatchee Bay site, Figures 5-21 and 5-22 suggest that while the differences in some of the estimation methods are

Table 5-11. Deterministic Model Parameters for Archer Landfill Site

Model Type	Cone Resistance (MPa) Estimate	Cone Resistance (MPa) Std Dev	Friction Resistance (kPa) Estimate	Friction Resistance (kPa) Std Dev
Log(Mean)	7.70	3.85-15.40	46.8	21.3-102.8
Log(Median)	8.62	4.69-15.82	49.7	26.0-95.1
Log(Trimmed Average)	8.09	5.13-12.76	49.9	31.5-78.9

Table 5-12. Regression Models for the Prediction of Cone Resistance at the Archer Landfill Site

Sounding	Model Type	R^2	RMSE
4	Model 1 (Log)	0.77	0.14
	Model 2 (Log)	0.81	0.13
	Low Term (Log)	0.81	0.12
	High Term (Log)	0.88	0.10
5	Model 1 (Log)	0.76	0.15
	Model 2 (Log)	0.80	0.14
	Low Term (Log)	0.84	0.13
	High Term (Log)	0.88	0.11
8	Model 1 (Log)	0.75	0.15
	Model 2 (Log)	0.79	0.14
	Low Term (Log)	0.83	0.13
	High Term (Log)	0.85	0.12

Note: The RMSE for the logarithmic approach was left in its transformed state to preserve its true value and meaning.

Table 5-13. Regression Models for the Prediction of Friction Resistance at the Archer Landfill Site

Sounding	Model Type	R^2	RMSE
4	Model 1 (Log)	0.77	0.16
	Model 2 (Log)	0.79	0.16
	Low Term (Log)	0.85	0.13
	High Term (Log)	0.90	0.11
5	Model 1 (Log)	0.78	0.17
	Model 2 (Log)	0.80	0.16
	Low Term (Log)	0.84	0.14
	High Term (Log)	0.89	0.12
8	Model 1 (Log)	0.78	0.17
	Model 2 (Log)	0.80	0.16
	Low Term (Log)	0.82	0.15
	High Term (Log)	0.85	0.14

Note: The RMSE for the logarithmic approach was left in its transformed state to preserve its true value and meaning.

Table 5-14. Results of Spatial Variability Study at Archer Landfill Site Using Transformed Data

ROOT MEAN SQUARE ERROR

METHOD	Q4	Q5	Q8	F4	F5	F8
MEAN	3.91	3.25	6.14	25.2	35.3	49.3
MEDIAN	4.21	3.17	5.74	25.4	34.1	48.3
TRIMMED AVG	4.02	3.18	5.96	25.4	34.0	48.2
WEIGHT (a/d)	2.36	5.05	3.79	13.0	30.8	31.8
WEIGHT (a/d2)	2.47	4.83	4.18	13.6	28.4	34.6
REG MODEL 1	2.14	3.42	3.11	13.0	13.4	24.4
REG MODEL 2	1.52	2.61	3.39	12.3	14.2	29.3
REG LO TERM	1.51	3.67	3.20	13.3	17.0	31.6
REG HI TERM	1.91	6.57	3.37	12.5	27.4	25.2
RANDOM FIELD	1.81	3.28	3.80	12.4	21.1	33.0
LINEAR INTERP	1.77	3.58	2.65	9.8	19.6	23.3

NOTE: Q4 = q_c at Sounding #4   F4 = f_s at Sounding #4
Q5 = q_c at Sounding #5   F5 = f_s at Sounding #5
Q8 = q_c at Sounding #8   F8 = f_s at Sounding #8

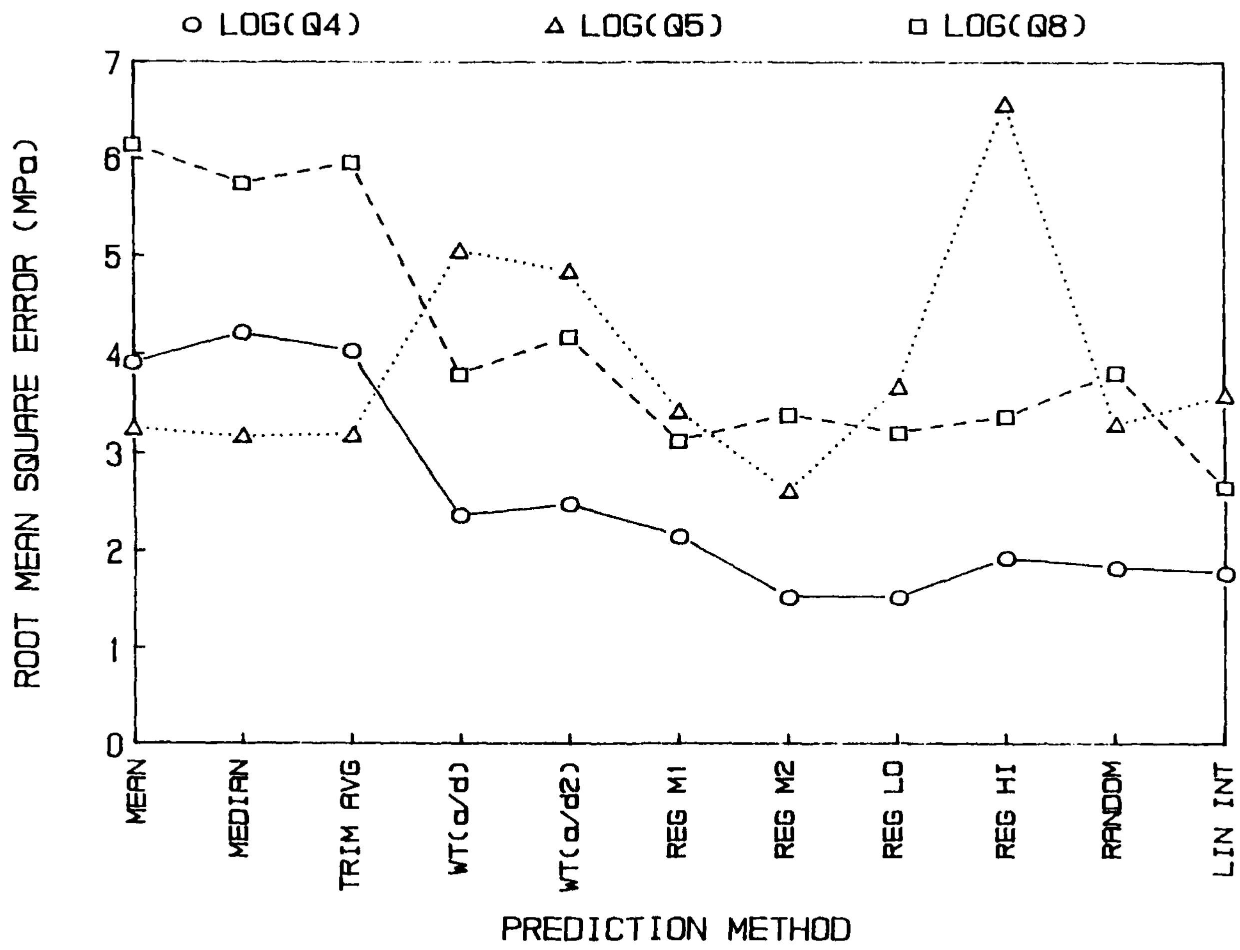


Figure 5-21. Prediction RMSEs for Cone Resistance at Archer Landfill

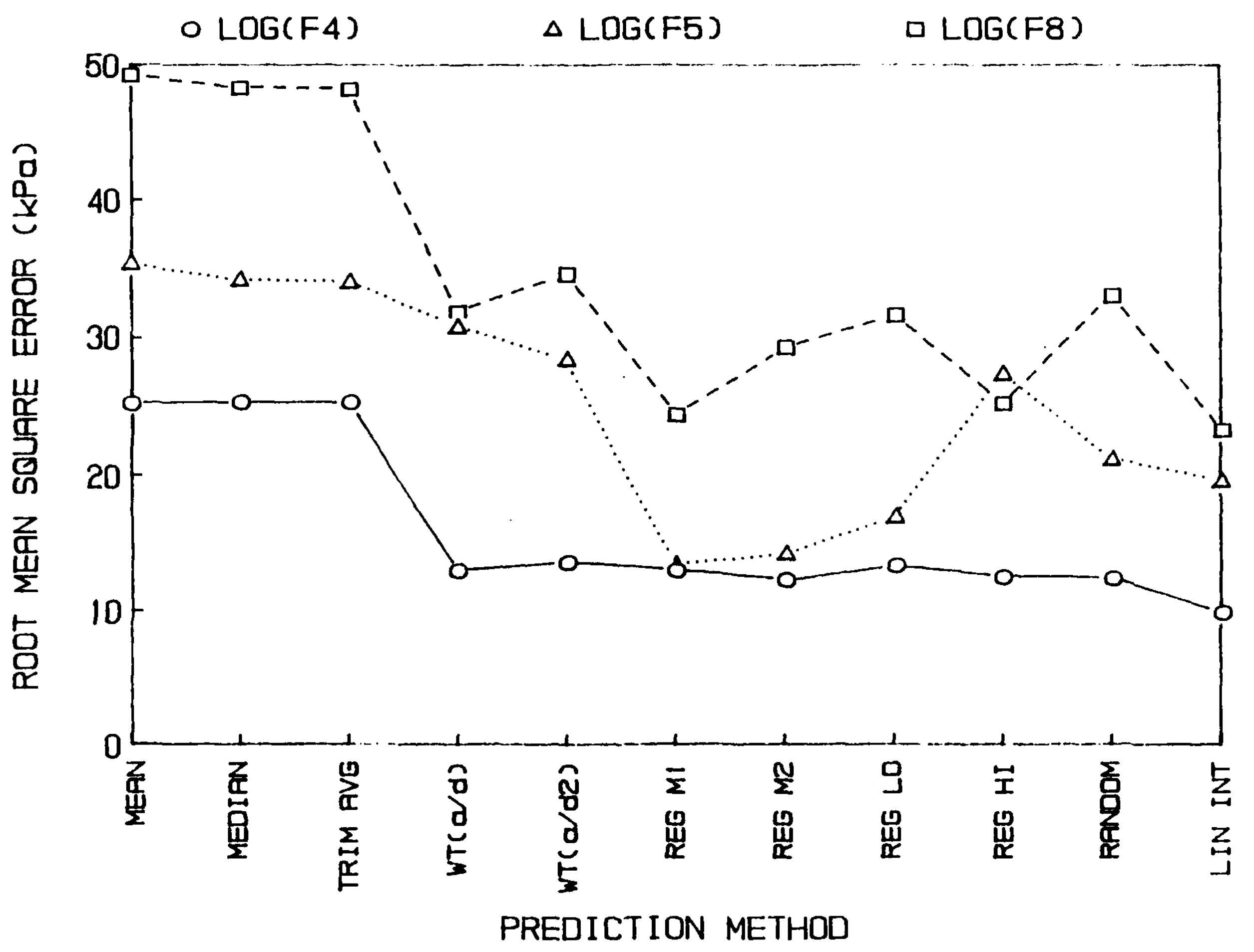


Figure 5-22. Prediction RMSEs for Friction Resistance at Archer Landfill

very small, overall the regression analyses performed as well as any of the other methods in predicting electronic cone penetrometer soundings (notwithstanding the anomalously high error rate for q_c at Sounding #5). All of the more sophisticated methods generally were able to improve on the error rate for the single-value methods. Additionally, the two straight weighting methods usually had higher RMSE's than did the regression, random field, or linear interpolation models.

To complete the evaluation of the various prediction methods at the Archer Landfill site, an inspection of plots of the actual predictions was made. Typical results are presented in Figures 5-23 and 5-24.

Figure 5-23 compares several of the distance-weighting methods, showing that the differences in the methods are indeed relatively minor. As has been observed at the other sites studied, most of the error occurs in stiffer strata, where the locations of the high-amplitude peaks, if present, may not coincide exactly with adjacent soundings.

Figure 5-24 compares the various regression models. As a result of the relative uniformity of the Archer Landfill site, all of the regression models are similar despite varying levels of order in the variables. Even the first order model, Model 1, can describe fairly well the gradually increasing magnitude in the soil property.

Discussion of Results

Autocorrelation function. The autocorrelation function is a conceptually appealing approach to quantifying the correlation structure in soil properties at a site. It's usefulness has been demonstrated by other researchers, primarily in the vertical direction. Wu notes that research in the horizontal direction has been limited due to lack of

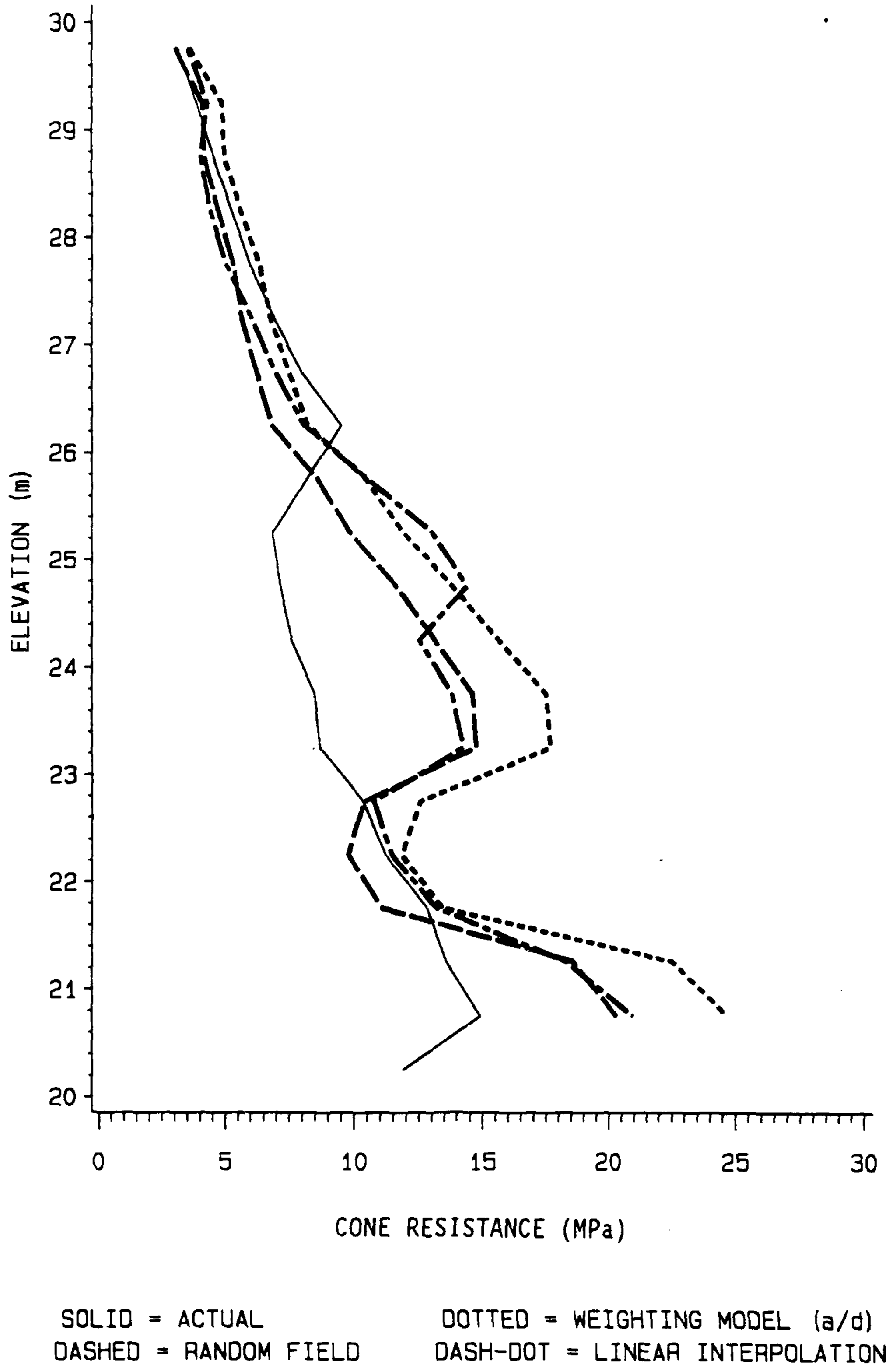
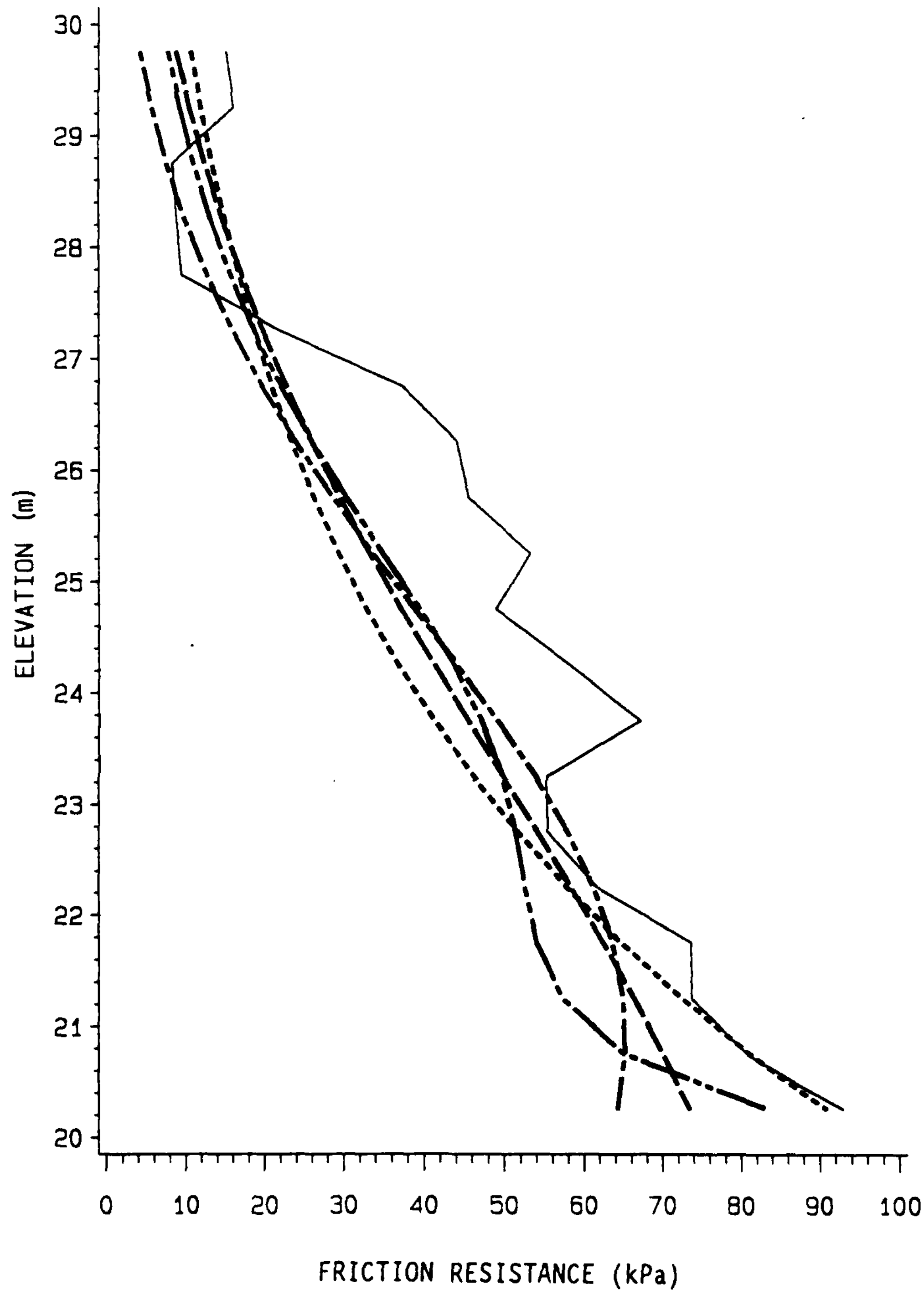


Figure 5-23. Prediction of q_c for Sounding #5 Using Various Distance-Weighting Models with Transformed Data at Archer Landfill



SOLID = ACTUAL DOTTED = MODEL 1 REGRESSION
DASHED = MODEL 2 REGRESSION DASH-DOT = LOW TERM REGRESSION
DASH-DOT-DOT = HIGH TERM REGRESSION

Figure 5-24. Prediction of f_s for Sounding #4 Using Various Regression Models with Transformed Data at Archer Landfill data (64). This study's attempts to improve this situation have not met with a great deal of success.

Generation of the autocorrelation function from the data set was reasonably straight-forward, following Kulatilake and Ghosh's recommended approach (26). Fitting a curve to the autocorrelation function likewise was not difficult, although scatter in the function made the selection of a fit somewhat subjective. The major objections to the autocorrelation function came in the results. The site with the longest range of 200 to 400 feet, Apalachicola River, proved to be virtually impossible to interpolate with any reasonable accuracy. The other two sites, with ranges between 50 and 100 feet, gave reasonably good predictions. Thus it would seem that the autocorrelation function on stationary residuals is not a reliable measure of a site's ability to be interpolated successfully. One reason for this incongruity is thought to be that the trend portion of the data at Choctawhatchee Bay and Archer Landfill (from the regression analysis) did a reasonably good job of describing the site, leaving relatively small residuals that were nearly random and uncorrelated. Apalachicola River, on the other hand, involved error rates that were so large that "large" residuals correlated fairly well with "large" residuals. Complicating any definitive conclusions is the fact that the Apalachicola River site involved SPT measurements, whereas the Choctawhatchee Bay and Archer Landfill sites were electronic CPT soundings. Studies at additional sites may be warranted.

The incorporation of the autocorrelation function into the random field model proved of limited utility. Despite its basis in stochastic theory, the model performed no better or worse than the other distance-weighting methods. The considerable additional work required to implement the random field model, especially when compared to simpler methods such as linear interpolation, cannot be justified based on the results of this study. It is conceivable that the model may prove applicable for shorter lateral distances, but the practical usefulness of such an application would be limited.

Logarithmic transformation. The use of a logarithmic transformation on the Florida data set was helpful in achieving some symmetry in the data by stretching out the large numbers of low-magnitude values while contracting the small numbers of unusually high-magnitude ones. While the transformation generally resulted in relatively minor changes in the error rate when compared with the untransformed approach, these changes tended to be for the better. Additionally, the transformed data generally resulted in more conservative (lower) predictions. A side benefit of the transformation was the prevention of negative predictions when using regression analysis.

The biggest objection to using the logarithmic transformation is the difficulty in interpreting the variability in the data. As a result of the transformation, the standard deviation would not be symmetrical about the mean or predicted value upon conversion back to conventional units. Despite this objection, if the logarithmic transformation results in a more symmetrical data set (as is did for the Florida data sets evaluated), then the logarithmic standard deviation would be a truer measure of the deviation in the prediction, and its use is encouraged.

Predictions. None of the prediction methods employed in this study consistently stood out as superior to the others. Nevertheless, several general trends were observed. Figure 5-25, which was used to demonstrate these trends, plots the average RMSE for each method, divided by the mean estimated using the 10% trimmed average on a transformed data set. This estimate of the mean was used to normalize the data for purposes of comparison because it had the smallest standard deviation of any of the single-value methods. In addition, Figure 5-25 plots the standard deviation for the average normalized mean, giving a relative estimate of the scatter in the errors.

The three single-value predictors (the mean, median, and trimmed average) were included in the study primarily as a gauge against which to judge the more sophisticated models. While differences between the three predictors were generally negligible, the other more sophisticated models usually produced lower root mean square errors. Therefore, use of the single-value approach for predicting penetration soundings is not recommended.

The distance-weighting methods, which were comprised of the two weight methods, the random field model, and linear interpolation, usually were indistinguishable from one another. No single approach could claim to be better than the others. The group as a whole produced competitive average RMSE's, but the scatter was sometimes rather large, raising some questions as to the reliability of the estimates.

The regression models generally produced among the lowest error rates. Of perhaps equal importance is the fact that, with few exceptions, the scatter in the error rates was relatively low when compared with the distance-weighting methods. This characteristic may

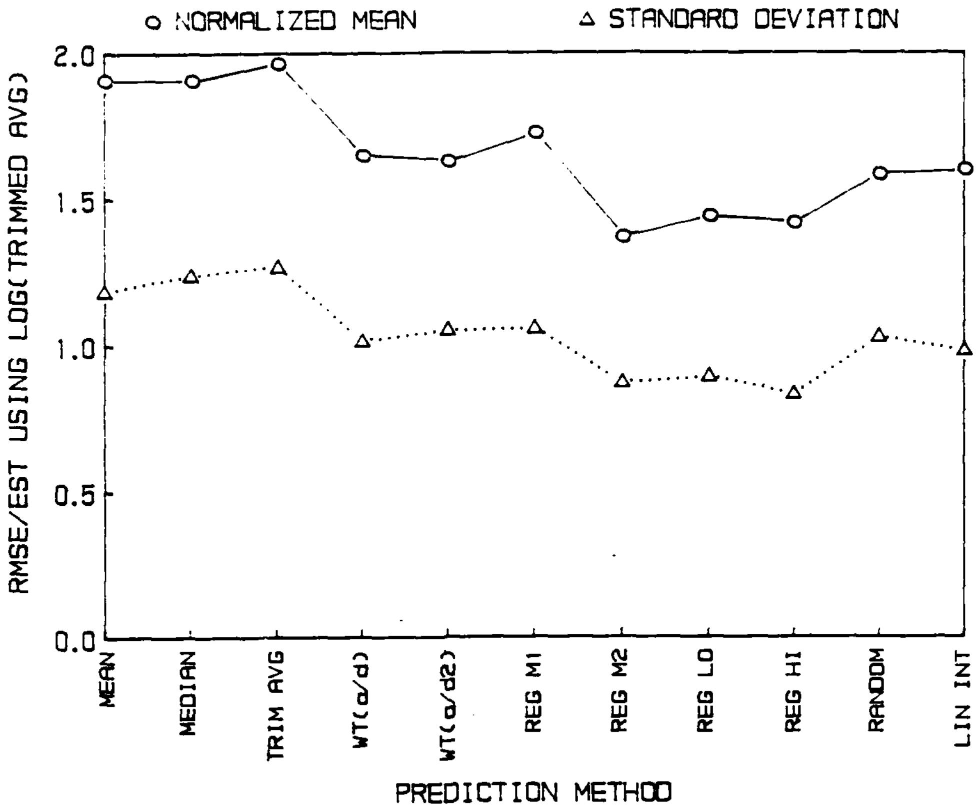


Figure 5-25. Comparison of Prediction Methods (Normalized)

be due to the lower influence that individual soundings have on the regression model, when compared with the distance-weighting models. Looking at the individual regression models, the Model 1 or linear regression generally had too few terms to adequately describe the soundings. The higher-order models typically did a good job of prediction, although no consistent advantage was seen in using the highest-order models (High Term Models). The stepwise model generator seemed effective in generating significant models and its use is recommended.

An additional benefit of the regression models is the calculation of the root mean square error. Table 5-15 summarizes how well the model root mean square error was able to estimate the actual RMSE obtained from the prediction. The Choctawhatchee Bay site model estimate was generally within 25% of the actual RMSE, with the model estimating higher (which would be conservative). The Apalachicola River site fared much more poorly, largely due to the very poor estimate for Boring #16. Discounting this one sounding, using the model RMSE would appear to usually be a reasonable, yet conservative approach to estimating one's confidence in the prediction.

The RMSE can also be used as a gauge of the likelihood of success in prediction. The model error rates from Choctawhatchee Bay and Archer Landfill were fairly low values, and the predictions were in general fairly good. The Apalachicola River error rates, on the other hand, were unacceptably large, and the subsequent predictions were (not surprisingly) poor. The RMSE may be a useful tool in designing the field exploration program and determining when an adequate number of soundings have been made.

Recall in Chapter 3 that the local standard deviation of electronic cone penetrometer soundings is estimated to be $0.5(q_c)$ to a maximum of 3.0 MPa for cone resistance, and $0.5(f_s)$ to a maximum of 24 kPa for friction resistance. A review of the root mean square errors for the two ECPT sites (Choctawhatchee Bay and Archer Landfill) suggest that the majority of the uncertainty is comprised of local variability--therefore, the prediction models (except for the single-value models) can all be judged to have done a good job of estimating the soundings. No similar judgment can be made at the Apalachicola River site due to no information on the local variability of SPT measurements.

<u>Recommendations</u>. Based on the results of this spatial variability study, the following approach is recommended for characterizing the soil properties at a site:

Table 5-15. Comparison of Regression Model RMSE with Prediction RMSE

PERCENT ERROR (Positive means model predicted higher)

LOCATION	SOUNDING	MODEL 1	MODEL 2	LO TERM	HI TERM	AVERAGE
Choctawhatchee	E	10.2	26.3	17.4	16.9	17.7
q_c (MPa)	H	19.0	5.0	-26.4	-36.9	-9.8
	J	-3.1	22.5	33.0	36.3	22.2
	SITE AVG	8.7	18.0	8.0	5.4	
	SITE STD	9.1	9.3	25.1	31.0	
Choctawhatchee	E	5.0	21.3	14.6	6.3	11.8
f_s (kPa)	H	34.7	26.1	19.0	4.0	20.9
	J	2.7	10.5	-6.8	-4.0	0.6
	SITE AVG	14.1	19.3	8.9	2.1	
	SITE STD	14.6	6.5	11.3	4.4	
Apalachicola	11	-14.1	-8.4	-23.6	-19.0	-16.3
N (blows/ft)	16	-88.8	-83.3	-89.6	-85.8	-86.9
	19	38.9	38.6	41.9	28.8	37.1
	SITE AVG	-21.3	-17.7	-23.8	-25.3	
	SITE STD	52.4	50.2	53.7	47.0	
	MODEL AVG	0.5	6.5	-2.3	-5.9	
	MODEL STD	35.4	34.3	38.0	35.4	

* Take measurements spaced at intervals small enough to generally characterize the site. The number of soundings will be determined by how rapidly the soil properties are changing spatially. This determination can be accomplished by graphically comparing the measured soil properties, or by performing a preliminary regression analysis. The regression analysis should include enough terms to generally describe the trends in the soundings--as a rule, up to second order horizontally and 2 to 5 or more orders vertically may be required. The squared multiple correlation coefficient (R^2) should hopefully be greater than 0.5 (may not be possible to attain at all sites), and the root mean square error (RMSE) from the regression analysis should be

reasonable. When deciding what RMSE's are reasonable, keep in mind the local variability of the device in question.

* Improvement in predictions can often be achieved by using data transformations. The goal of the transformation should be to achieve a degree of symmetry in the measured values. Different transformations are available, depending on the nature and strength of the transformation required. Common transformations to expand lower numbers include (in order of increasing strength) square roots, logarithms, and negative reciprocals. To expand larger numbers, powers of two or more can be used. A good elementary statistics text can provide additional information on transforming data sets.

* Once the data are collected and transformed as required, inspect the data for high-frequency spikes (say several spikes over a 0.5 meter increment). If the spikes exist and the number of data points are large (as is typical for electronic friction-cone penetrometer data) then a data filter is recommended. Taking the average value over each 0.5 meter increment and assigning this value to the midpoint of the increment seemed to work well for the penetrometer data used in this study.

* Assuming a reasonable number of soundings is available, regression analysis is recommended to develop a mathematical model for the site. Use of a stepwise model generator is also encouraged to insure that all variables in the model are significant and contributing. This model can then be used to interpolate soundings at other locations within the range of the data. If too few soundings exist to develop a regression model, then simple linear interpolation can be used (especially if the soundings have similar profiles).

* To estimate the average error in the prediction, use of the RMSE from the regression analysis is recommended (if linear interpolation is used, the RMSE must be estimated). In no case should the RMSE be less than the local variability of the device being used (determined separately). Recall Equation 4-4, which states that the total variance is equal to the sum of the individual contributing variances. Since the RMSE is an estimate of the standard deviation in the regression model, then its square (called the mean square error, or MSE) is an estimate of the model's variance. The local MSE can be subtracted from the regression MSE and the two treated separately--this would permit the estimation of lower error rates for low-value measurements. As an example, consider the prediction of q_c at Sounding J of Choctawhatchee Bay. Using the Low Term regression model

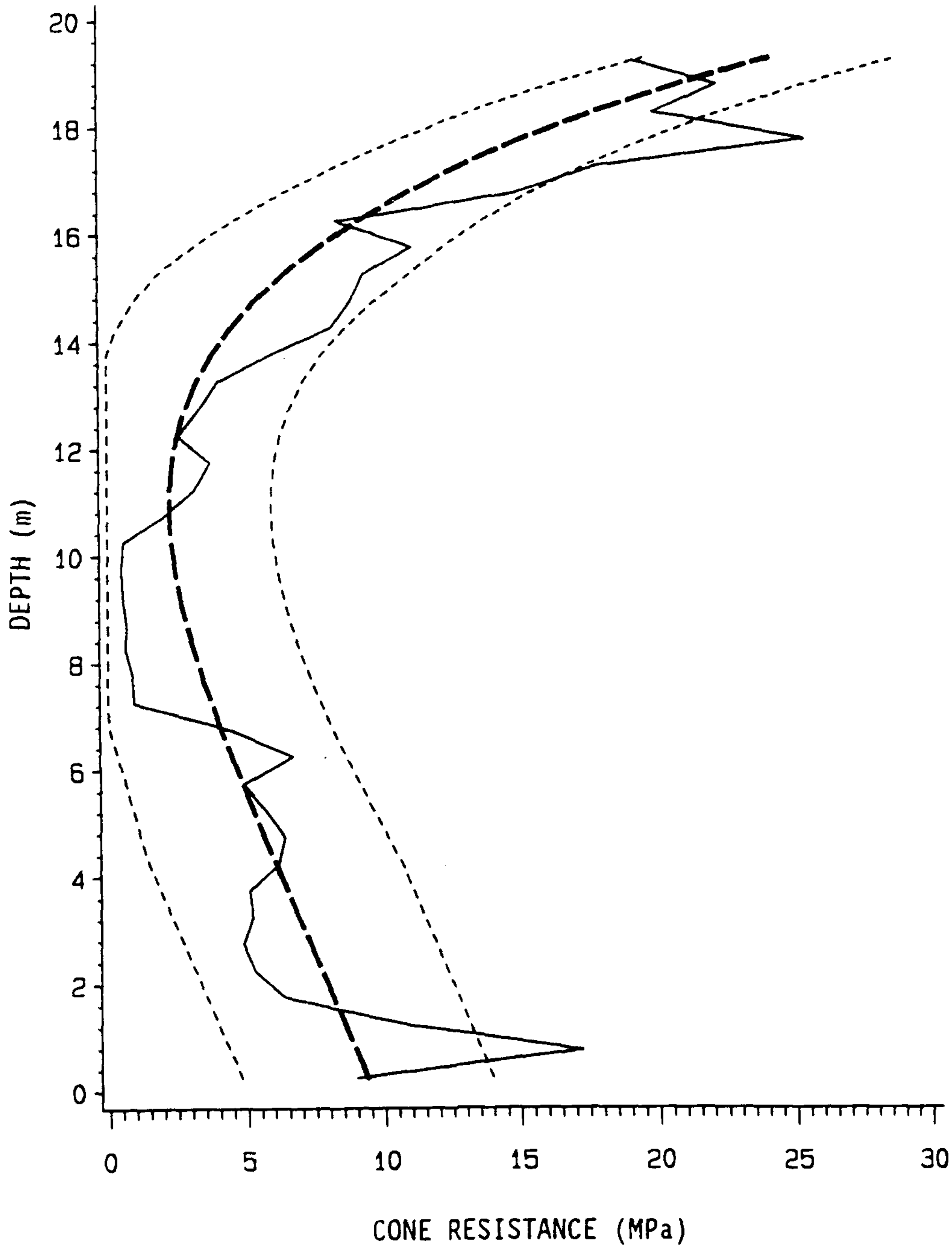
$$\text{Model RMSE} = 4.58 \text{ MPa} \qquad \text{Model MSE} = 21.0 \ (\text{MPa})^2$$

$$\text{Local RMSE} = 3.00 \text{ MPa} \qquad \text{Local MSE} = 9.0 \ (\text{MPa})^2$$

$$\begin{aligned} \text{Spatial Variability MSE} &= \text{Model MSE} - \text{Local MSE} \\ &= 12.0 \ (\text{MPa})^2 \end{aligned}$$

$$\begin{aligned} \text{Predicted MSE} &= \text{Local MSE} + \text{Spatial Variability MSE} \\ &= [0.5(q_c)]^2 + 12.0 \ (\text{MPa})^2 \quad \text{for } q_c \leq 6 \text{ MPa} \\ &= (9.0 + 12.0) \ (\text{MPa})^2 = 21.0 \ (\text{MPa})^2 \quad \text{for } q_c > 6 \text{ MPa} \end{aligned}$$

The predicted RMSE would simply be the square root of the predicted MSE. Note that the minimum possible q_c of 0 MPa is a limiting value. Figure 5-26 plots the RMSE bands for the example sounding.



SOLID = ACTUAL
DOTTED = RMSE LIMITS
DASHED = LOW TERM REGRESSION

Figure 5-26. Example of Average Error Estimate--Prediction of q_c at Choctawhatchee Bay Sounding J Using Low Term Regression

CHAPTER 6
COMPARISON OF 10-TON AND 15-TON FRICTION-CONE PENETROMETER TIPS

Introduction

Approximately 30% of the electronic cone penetrometer soundings performed for this research project were made using the University of Florida's 15-ton penetrometer tip, whose physical size is larger than the standard 10-ton (or 5-ton) tip. The local variability study of Chapter 3 suggested that the 15-ton tip's repeatability was comparable to that of the 5-ton and 10-ton. There was concern, however, that the actual magnitude of the measurements between the devices may not be exactly comparable. This concern stemmed not only from the physical size difference between the penetrometer tips, but also from the difficulties encountered with the 15-ton tip's friction resistance measurements (as discussed in Chapter 2). The latter reason presented a greater concern, as Meigh notes that cones ranging in projected areas from 500 to 1500 mm^2 (0.78 to 2.33 in^2) do not differ significantly in their measured results (34). In anticipation of using the 5-ton, 10-ton and 15-ton penetrometer measurements for the soil classification study, an evaluation of the devices' comparability was undertaken.

The purpose of this phase of the research is to compare measurements made with the UF 15-ton penetrometer tip with those made by the UF 10-ton and 5-ton tips (Note: a similar study between the standard-size 5-ton and 10-ton tips was not undertaken due to lack of sufficient data in the data base--however, neither tip "stood out" from one another, suggesting comparability between the 5-ton and 10-ton tips). The approach used was nearly identical to that used for the local variability study of Chapter 3. 5-ton and 10-ton ECPT soundings were paired with 15-ton soundings that were nearby. Then using graphical and statistical techniques, the differences in the pairs were described and quantified. The "digital filter" described in Chapter 3 was used to help insure any measured differences were truly representative of the data.

Size Comparability Study Data Base

The research project data base was searched for pairs of ECPT soundings that met two criteria: the soundings must be no more than 4.6 meters (15 feet) apart, and different size penetrometer tips must have been used in each sounding. The distance criteria was admittedly somewhat arbitrary, and represented an attempt to include a representative number of sounding pairs in the analysis, while hopefully insuring that the tips were testing the "same" material. The resulting data base used in the size comparability study is summarized in Table 6-1.

The minimum spacing was determined to be 44 cm (17 in), based on Robertson and Campanella's recommendation of 10 hole diameters from open boreholes and excavations, to allow for potential radial stress relief effects (41). As a check on the maximum selected spacing of 4.6 meters, the sounding pairs were graphically overlaid and evaluated as to the likelihood that the material was approximately the same. If reasonable doubt existed, the sounding was discarded from further analysis. Note that separation distances varied between 0.4 and 4.3 meters (1.4 and 14 feet).

Table 6-1. Data Base for Size Comparability Study

Location (ID)	10-TON TIP	15-TON TIP	Separation Distance (ft)	Comments
Fort Myers (FMYER)	C010D	C010F	14.0	C010D = 5-ton
Jacksonville (JAXa)	C027A	C027C	5.0	q_c only
Jacksonville (JAXb)	C027B	C027C	5.0	q_c only
Jacksonville (JAXc)	C028B	C028A	6.0	q_c only
Overstreet (OVRST)	C004A	C004B	4.6	q_c only
Sarasota Garage (SGAR)	C006A	C006B	1.4	
West Palm Beach (WPBa)	C015A	C015C	8.4	
West Palm Beach (WPBb)	C015B	C015C	11.2	
West Palm Beach (WPBc)	C017B	C017A	7.9	

The q_c data were comprised of 3056 observations, whereas the f_s data had 1839 observations. The same data filter introduced in Chapter 3 was employed to remove the high-frequency noise from the data. Figure 6-1 shows the filtered cone resistance data plotted about the expected 1:1 line. Most of the data are relatively well-behaved about the line, and display a fairly constant variance. Figure 6-2 shows a similar plot for the friction resistance data. This figure suggests that the 10-ton penetrometer tip measures higher values for friction resistance when compared with the 15-ton tip, especially for friction values below 100 kPa (the bulk of the data).

Evaluation of Data Scatter

To evaluate the data scatter, regression analysis using the REG procedure of the SAS system was used. Both the complete data set and the filtered data were evaluated. The models used in the analysis were

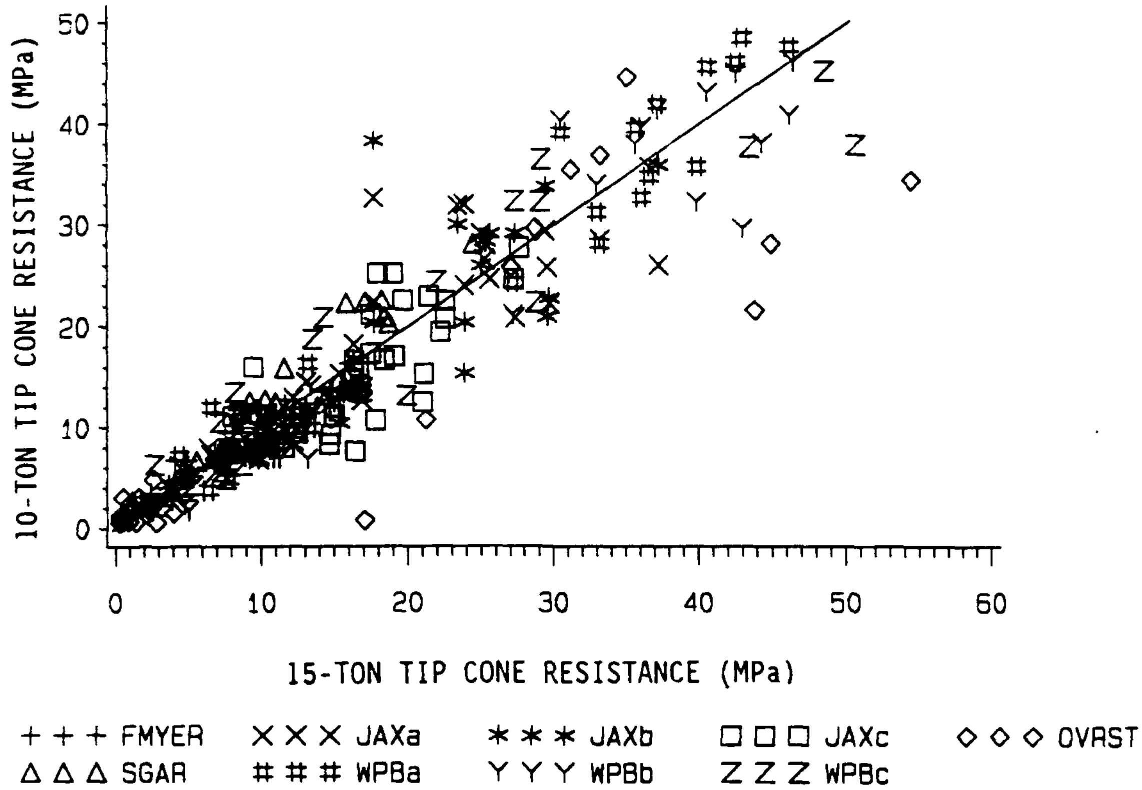


Figure 6-1. Cone Resistance Data for Size Comparability Study

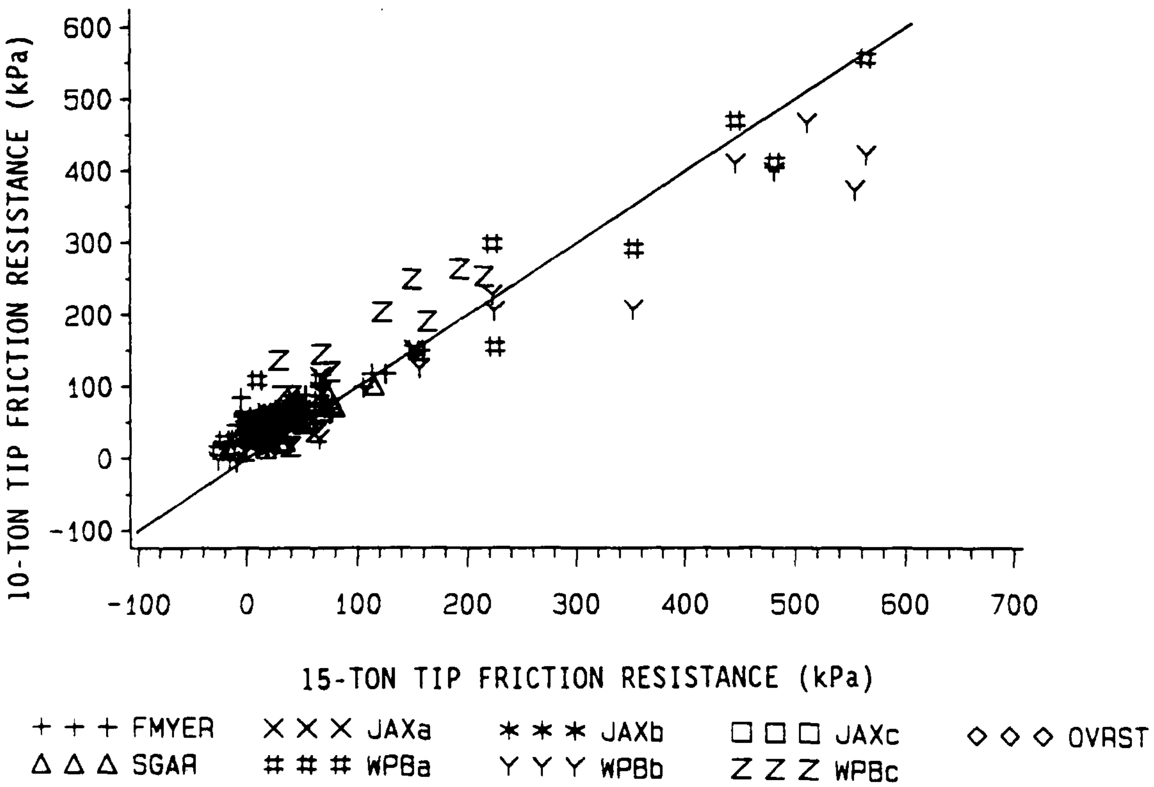


Figure 6-2. Friction Resistance Data for Size Comparability Study

$$(q_c)_{10} = b_0 + b_1(q_c)_{15} \quad \text{(6-1)}$$

$$(f_s)_{10} = b_0 + b_1(f_s)_{15} \quad \text{(6-2)}$$

The results of the size comparability study are summarized in Table 6-2.

Table 6-2. Results of Size Comparability Study

Parameter (units)	Filter	Avg Diff (10t-15t)	b_0	b_1	RMSE
Cone Resistance (MPa)	No	-0.59	1.16	0.90	5.70
	Yes	-0.54	0.68	0.92	4.42
Friction Resistance (kPa)	No	15.2	31.9	0.78	44.2
	Yes	15.2	29.5	0.80	29.5

The root mean square errors obtained from the regression analysis on the filtered data are larger, but comparable to the errors obtained from the local variability study (3.0 MPa for q_c, and 24 kPa for f_s). More troubling, however, is the obvious bias in the friction resistance measurements as shown in Figure 6-2. This bias helps to explain some of the problems encountered with the UF 15-ton penetrometer tip, especially concerning persistent negative friction readings in soft soils.

Based on the results of the size comparability study coupled with the history of problems with the 15-ton tip, the 10-ton data set is judged superior (and hence not completely comparable with the 15-ton data). Therefore data collected with the University of Florida 15-ton penetrometer tip should not be mixed with other data until the cause of the discrepancy can be isolated and quantified.

CHAPTER 7
CLASSIFICATION OF FLORIDA SOILS USING THE ECPT

Introduction

For any project requiring deep foundations, knowledge of the underlying soil types and site stratigraphy is of paramount importance. To obtain this information a site investigation is typically undertaken, usually consisting of some combination of soil borings, sampling, and standard penetration testing. However, the electronic cone penetration test (ECPT) offers some significant advantages over the more common site investigation methods (34,35):

1. Soil borings, sampling, and the SPT are more expensive than the ECPT, and much slower.
2. The ECPT provides a virtually continuous record of the sounding, often permitting identification of very thin layers.
3. Disturbance of the ground is minimized.

The electronic friction-cone penetrometer is not without disadvantages, however, including

1. The lack of a physical sample to verify the indirect classification of soil by the ECPT.
2. A limited ability to penetrate very stiff soil layers.
3. The requirement for careful use and maintenance of the sensitive electronic equipment.

In the classification of soils, the usual schemes employ descriptive categories based on visual and textural properties (clay, silty clay, shelly sand, etc.), or a structured classification system based on measured index properties. The most commonly used soil classification system in the United States is the Unified Soil Classification System (USCS), which employs grain size distribution and Atterberg limits tests on remolded soil samples to classify the soil into distinct groups (15). The American Society of Testing and Materials (ASTM) Standard D2487 provides details on applying the USCS (2).

Classification of soil by the ECPT, however, is based on in situ soil behavior, as measured by the cone resistance, q_c, and the friction resistance, f_s. Classification into "familiar" categories is attempted by the use of classification charts; however, obvious difficulties are encountered when trying to correlate in situ soil behavior to observed physical characteristics or to somewhat arbitrary index parameters on remolded soil samples. For example, Olsen and Farr point out that a CL (low plasticity clay) classification in the USCS becomes an SC (clayey sand) if the percent passing the US Number 200 sieve changes from 50.1% to 49.9%, a negligible difference with regards to the soil's strength behavior (35).

The purpose of this phase of the research is to evaluate existing classification charts for their applicability to soils indigenous to Florida, and to recommend modifications as required. To accomplish this objective, cone penetrometer soundings were made at some 27 locations where nearby SPT boring logs (which include soil identification) were available. In addition, laboratory analyses were either performed or obtained on a limited subset of soil samples from the SPTs as a means of evaluating the accuracy of the boring log classifications. Using this data base, two types of discriminant analysis were employed to statistically analyze the data base, and determine the "best" ECPT classification system for Florida soils.

Current Practice

Measurement Considerations

In employing the electronic friction-cone penetrometer for identification of soil types, the challenge is to use two (or three in the case of a piezocone) stress measurements to discriminate an often large number of discrete soil categories. In addition to the difficulties presented by the often arbitrary classification boundary lines dividing up a soil continuum, one is also faced with overlapping zones of soil behavior compounded by natural randomness. Despite these obstacles, the ECPT enjoys a good reputation as an indirect soil classification technique.

As an aid to amplifying the differences in strength behavior between different types of soil, the friction ratio, R_f, is typically used:

$$R_f = f_s/q_c \quad \text{(in percent)} \qquad \text{(7-1)}$$

This ratio is very useful in distinguishing soil types because frictional stress in fine-grained soils is typically a larger percentage of the total stress acting on the penetrometer than in coarser soils. In an early use of the cone penetrometer (mechanical) for soil identification, Begemann employed only the friction ratio. He classified soils with an R_f below 2.5% as sands, over 3.5% as clays, and 2-4% as silts or soil mixtures (35). Current classification schemes typically plot q_c against R_f to permit greater differentiation of soil types.

Other considerations in using the ECPT for soil identification result from the physics of penetrating soil with a probe. The resistance measured by the cone penetrometer is influenced by the soil some 5-10 cone diameters above and below the tip, with this influence extending further for stiffer soils (34,42). This phenomenon may cause some imprecision when using the cone penetration test to identify thin soil layers and soil interfaces. Also, several authors have cited evidence indicating overburden pressure may influence the cone and friction resistance readings (34,35,36). Meigh notes that the friction ratio may decrease for some fine-grained soils with increasing depth. Olsen and Malone recommend normalizing q_c, f_s and R_f readings to a vertical effective stress, p'_v, of 1 tsf as follows:

$$q_{cn} = q_c/(p'_v)^n \quad \text{.......................(7-2)}$$

$$f_{sn} = f_s/(p'_v) \quad \text{.......................(7-3)}$$

$$R_{fn} = f_{sn}/q_{cn} \quad \text{.......................(7-4)}$$

in which n is an exponent value ranging from 0.60 for coarse sands to almost 1 for clays, and 0.75-0.90 for soil mixtures and silts. Olsen and Malone use this exponent value to account for the stress bulb in front of the cone increasing at a less than linear rate with increasing vertical effective stress.

Typical Classification Systems

ECPT classification systems are typically embodied in two-dimensional charts plotting cone resistance, q_c, against friction ratio, R_f. While all of the charts contain common features (such as locating sand at high q_c and low R_f values), the details and complexities of the charts differ. For example, Figure 7-1 is a simple chart employing uncorrected values of $\log(q_c)$ and R_f to identify general soil types.

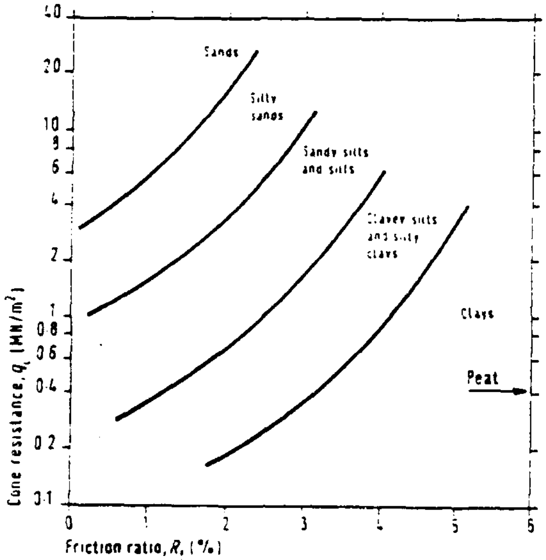


Figure 7-1. Robertson and Campanella's Simple Soil Classification Chart (after Meigh, (34)) (Used with permission of CIRIA)

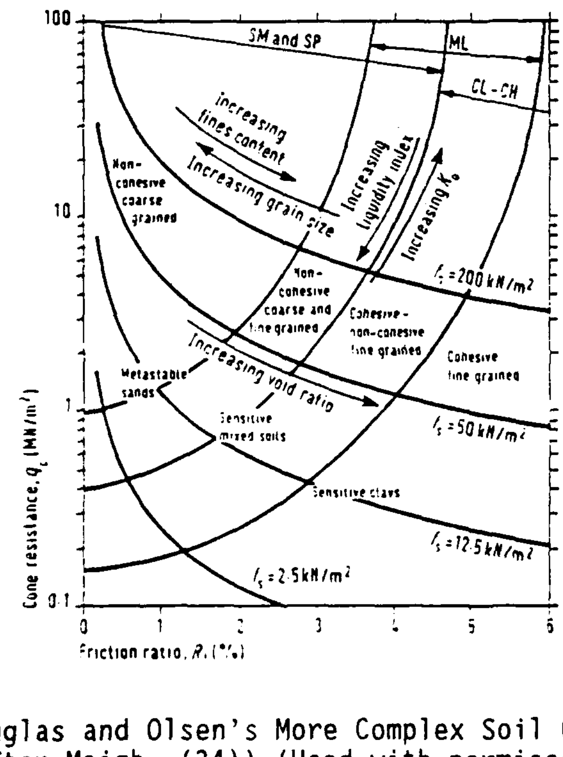


Figure 7-2. Douglas and Olsen's More Complex Soil Classification Chart (after Meigh, (34)) (Used with permission of CIRIA)

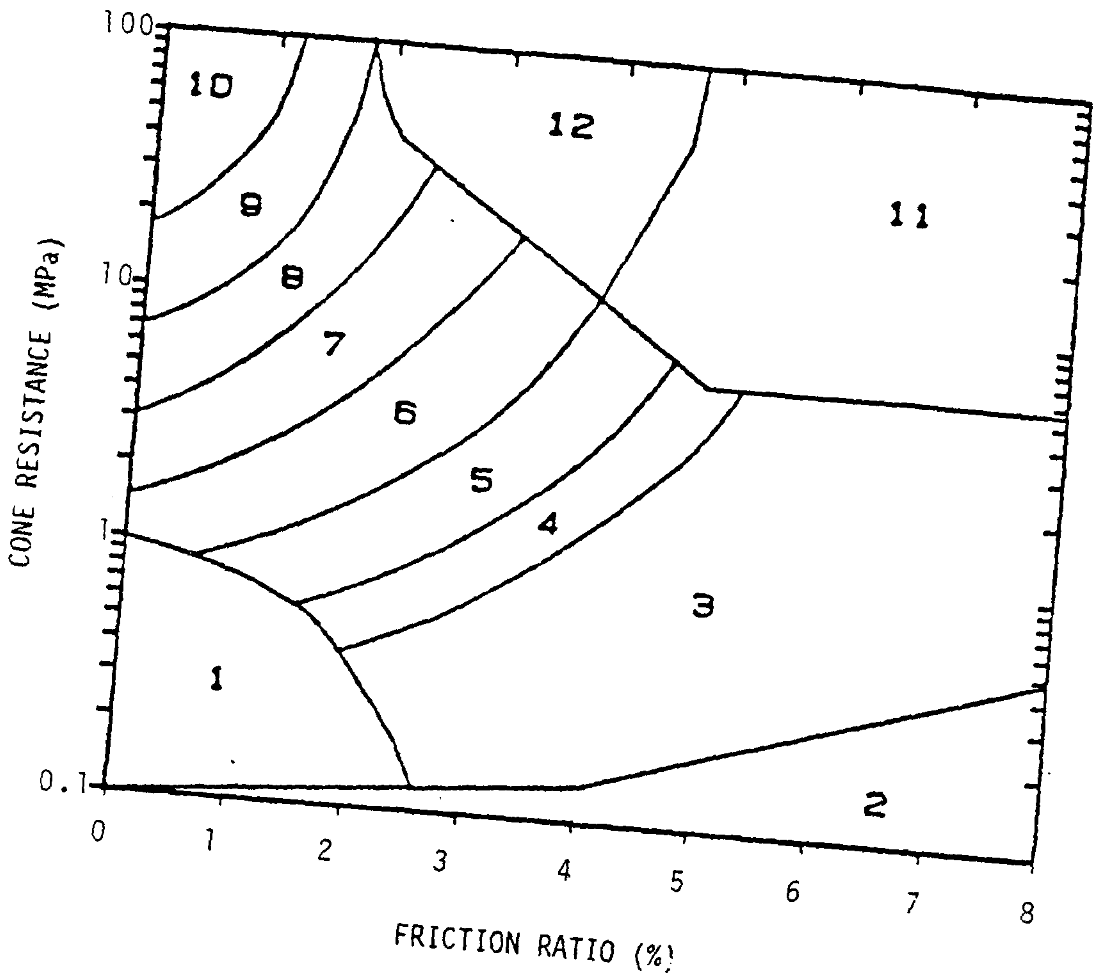
This is a working version of a much more complex earlier classification chart, shown in Figure 7-2. This chart indicates expected trends in several index parameters and suggests possible classifications from the Unified Soil Classification System.

Figure 7-3 shows a classification scheme employing discrete boundaries for twelve identified soil types. Such a scheme is attractive for its ease of interpretation and potential for computer implementation, but may be too inflexible unless modified for local applications. Figure 7-4 is a recent chart which attempts to account for vertical effective stress effects by employing normalized cone measurements. This chart uses a horizontal log scale to accentuate the lower friction ratio values, and also suggests equivalent USCS ranges as did Figure 7-2.

Analysis Approach

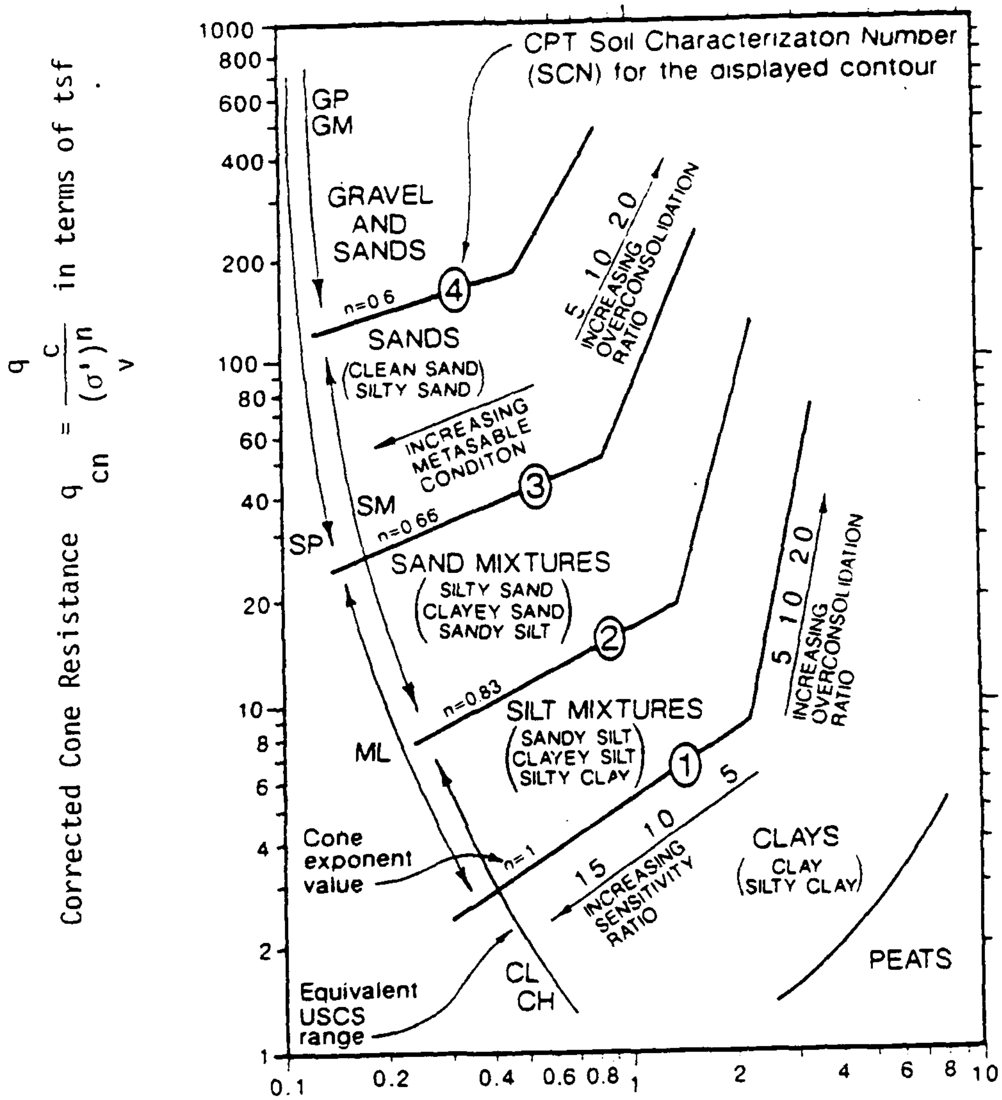
Data Base Creation

A large data base was created to evaluate the use of the electronic cone penetration test for soil classification in Florida. The basic approach was to collect ECPT data near available SPTs, and then carefully match the ECPT measurements with the SPT soil descriptions. A maximum separation distance of 7.6 m (25 ft) was selected (somewhat arbitrarily) to help insure the ECPT soil types were the same as the SPT soils. Data were rejected from the analysis if there existed a reasonable doubt that the cone measurements represented the soil layer described in the boring log. This data base represented 27 soundings in 8 Florida cities. Some 15 different soil types were identified, as shown in Table 7-1. These soil types were combined into 7 major



Zone	Soil Behavior Type
1	Sensitive fine grained
2	Organic material
3	Clay
4	Silty clay to clay
5	Clayey silt to silty clay
6	Sandy silt to clayey silt
7	Silty sand to sandy silt
8	Sandy to silty sand
9	Sand
10	Gravelly sand to sand
11	Very stiff fine grained*
12	Sand to clayey sand*
*	overconsolidated or cemented

Figure 7-3. Discrete Soil Classification Chart (after Robertson et al., (44)) (Used with permission of ASCE)



Corrected Friction Ratio (%) in terms of tsf

$$R_{fn} = \frac{f_{sn}}{q_{cn}} 100 = \frac{f_s/\sigma'_v}{q_c/(\sigma'_v)^n} 100 = \frac{f_s}{q_c} \frac{1}{(\sigma'_v)^{(1-n)}} 100$$

Figure 7-4. Soil Classification Chart Normalized for Overburden (after Olsen and Malone, (36)) (Reprinted from: J. de Ruiter (ed.), Penetration testing 1988--Proceedings of the first international symposium on penetration testing, ISOPT-1, Orlando, 20-24 March 1988, Volume 2, 1988, 1096 pp., 2 volumes, Hfl.295/US$147.50. A.A. Balkema, P.O. Box 1675, 3000 BR Rotterdam / A.A. Balkema, Old Post Road, Brookfield, Vermont 05036.)

categories, also shown in Table 7-1. This grouping was based on the verbal descriptions of the soils categorized by the Unified Soil Classification System, as presented in ASTM Standard D 2487, and as discussed by Perloff and Baron (2,39). Table 7-2 summarizes the source of the data used for this portion of the research. Details on the soundings are contained in Appendix A and Knox (25).

Table 7-1. Soil Types in Classification Data Base

ID#	Soil Type	Category	Number of Observations	Percent of Total Data
2	Organic Material	O (Organic)	26	0.3
3	Clay	C (Clay)	368	4.6
7	Silty Sand-Sandy Silt	M (Silt)	150	1.9
8	Sand-Silty Sand	T (Silty Sand)	2098	25.9
9	Sand	S (Sand)	2924	36.3
13	Shelly Sand	S (Sand)	168	2.1
14	Sandy Clay	C (Clay)	298	3.7
15	Sandy Clay with Shell	C (Clay)	10	0.1
16	Clayey Sand	U (Clayey Sand)	1047	12.9
17	Clayey Sand with Shell	U (Clayey Sand)	481	5.9
19	Sand with Organics	S (Sand)	26	0.3
21	Clay with Shell	C (Clay)	18	0.2
23	Weathered Rock	R (Rock)	43	0.5
29	Cemented Sand	S (Sand)	269	3.3
30	Cemented Clayey Sand	U (Clayey Sand)	161	2.0
			8087	100.0

In addition to the ECPT data, laboratory analysis of 69 SPT soil samples was performed and correlated with electronic cone penetration test measurements. The purpose of this analysis was to provide "exact" soil classifications to compare with the ECPT measurements, and to provide a means of qualitatively verifying the soil identifications contained in the SPT field logs. The samples were classified by the Unified Soil Classification System, as applied in ASTM D2487 (2). To insure accurate representation of a sample's ECPT measurements, only samples with nearly constant q_c and f_s values over the sample's length were used, as recommended by Olsen and Farr (35). Table 7-3 summarizes the results of the laboratory analyses, details of which are presented in Appendix C.

Table 7-2. Soil Classification Data Base

SITE	ECPT #	SPT #	ECPT-SPT DISTANCE
Sarasota Garage	C006A	S006A	7.6 m (25 ft)
Fort Myers Interchange	C010D	S010A	4.8 m (16 ft)
West Palm I-95	C015A	S015A	4.5 m (15 ft)
	C015B	S015A	7.1 m (23 ft)
	C016C	S016A	6.3 m (21 ft)
	C017B	S017A	4.5 m (15 ft)
Choctawhatchee Bay	C019B	S019A	1.2 m (4 ft)
	C019G	S019C	5.2 m (17 ft)
	C019J	S019B	4.4 m (14 ft)
	C019K	S019B	5.0 m (16 ft)
	C020B	S020A	1.5 m (5 ft)
	C021D	S021A	4.7 m (15 ft)
White City	C022A	S022A	7.6 m (25 ft)
	C022B	S022B	1.6 m (5 ft)
	C022C	S022C	3.0 m (10 ft)
Orlando Arena	C023A	S023A	7.4 m (24 ft)
	C023C	S023C	7.3 m (24 ft)
	C023D	S023E	1.5 m (5 ft)
Orlando Hotel	C024A	S024A	2.2 m (7.4 ft)
	C024B	S024B	3.1 m (10 ft)
	C026A	S026A	4.3 m (14 ft)
Jacksonville Coal Terminal	C028B	S028A	See Note
West Bay	C030A	S030A	2.7 m (9 ft)
	C030B	S030B	0.6 m (2 ft)
	C030C	S030C	7.2 m (24 ft)
	C030D	S030D	2.9 m (10 ft)
	C030F	S030F	5.6 m (18 ft)

Note: Exact location of SPT undetermined, but believe distance criteria met. Inspection of data supports belief that soils were correctly identified.

Table 7-3. Summary of Laboratory Tests on SPT Samples

SITE	USCS CLASSIFICATION	ANALYSIS CATEGORY	NUMBER OF OBSERVATIONS
Sarasota Garage (Site 006)	SM	T	3
	SP-SM	T	2
Sarasota Condo (Site 008)	SM	T	3
Fort Myers Airport (Site 012)	ML	M	1
	SC	U	1
Choctawhatchee Bay (Site 019-021)	CH	C	3
	SM	T	3
	SP-SM	T	1
	SP	S	6
White City (Site 022)	SM	T	6
	SP-SM	T	8
	SP	S	3
Orlando Hotel (Site 024-026)	SC	U	2
West Bay (Site 030)	ML	M	3
	SM	T	6
	SP-SM	T	10
	SP	S	5
Lake Wauberg (Site 031)	CH	C	1
	MH	M	2
SUMMARY	CH	C	4
	MH, ML	M	6
	SC	U	3
	SM, SP-SM	T	42
	SP	S	14
			69

Discriminant Analysis

Dillon defines discriminant analysis as "a statistical technique for classifying individuals or objects into mutually exclusive and exhaustive groups on the basis of a set of independent variables" (14, p. 360). For this phase of the research, the groups are either soil types or the more general soil category, and the independent variables are measurements of cone resistance, q_c, and friction ratio, R_f (Note that friction resistance measurements are not independent of q_c and R_f). Two discriminant analysis techniques were used for analyzing the soil classification data base: a parametric approach, and a nonparametric approach.

Parametric approach. The parametric approach was implemented using the DISCRIM Procedure of the SAS System (48). The term parametric implies that assumptions are made on the distribution of the data; specifically, the distribution of data is assumed to be approximately multivariate normal. Using this assumption, DISCRIM calculates a vector for each group (for each soil type or category in this case) which contains the means of the variables (q_c and R_f, for example) for all members of that group. A generalized squared distance (a conceptual distance based on the values of the independent variables) between an observation and each of the mean vectors is then calculated. The observation is classified into that group that is closest (i.e., has the smallest generalized squared distance).

The generalized squared distance, $D_t^2(x)$ from an observation vector, x, to group t is

$$D_t^2(x) = (x - m_t)'S^{-1}(x - m_t) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7\text{-}5)$$

in which m_t = mean vector for group t

S = pooled covariance matrix

The covariance matrix accounts for correlations between the independent variables. This prevents two variables that are highly correlated from contributing as much information as a third, truly independent variable (32). The parametric approach assumes that the within-group covariance matrices are all equal, and represented by this pooled matrix.

<u>Nonparametric approach</u>. The nonparametric approach was implemented using the NEIGHBOR Procedure of the SAS System (48), which performs a k-nearest-neighbor discriminant analysis. The term nonparametric implies that no assumptions are made on the distribution of the data. The NEIGHBOR procedure calculates the Mahalanobis distance between an observation and all other observations. Classification of the observation is based on the group containing the highest proportion of the k nearest neighbors:

$$d^2(x_1, x_2) = (x_1 - x_2)'S^{-1}(x_1 - x_2) \quad \text{(7-6)}$$

in which x_1 and x_2 are two observation vectors, and **S** is the pooled covariance matrix. For all analyses in this project, a k of 5 was used.

Results and Discussion

Data Transformation

Implementation of the parametric approach for discriminant analysis assumes the independent variables to be approximately normally distributed. Also, the within-group covariance matrices are assumed equal. While many worthwhile analyses have been undertaken in violation of the basic assumptions of discriminant analysis, the results of such analyses may be questionable, and caution is advised in interpreting the results. In particular, the analysis may be overly sensitive to small sample sizes, and the tests of significance and estimated classification error rates may be biased. While the overall error rate may be little affected, individual group error rates may be significantly in error (14,32).

To better approximate a normally-distributed data set, a logarithmic data transformation was used. During exploratory data analysis of the cone measurements, virtually all of the different soil types exhibited a frequency distribution that appeared to approximate a log-normal distribution. Such a distribution would cause estimates of the mean to be nonrepresentative of the bulk of the data. To improve the symmetry of the data set, base-10 logarithms of the cone resistance and friction ratio values were used, resulting in better estimates of the center of the distribution. A typical effect of the data transformation was previously demonstrated in Figure 5-1.

Data Sets

Four data sets were evaluated using both the parametric (SAS's DISCRIM procedure) and the nonparametric (SAS's NEIGHBOR procedure) discriminant analysis approaches. The first data set was the laboratory classification data. These data were then normalized to an effective overburden pressure of 96 kPa (1 tsf) using Olsen and Malone's approach to produce the second data set (Appendix E describes the computer approach used). An average total unit weight of 17.3 kN/m^3 (110 pcf) was assumed for the soil. These two data sets were used to evaluate the accuracy of the driller's field classifications from the SPT tests. They were also used to compare the results of discriminant analysis using raw versus normalized data.

Once the initial evaluation on a small data set was complete, discriminant analysis of the full data set (as presented in Tables 7-1 and 7-2) was undertaken. The third data set contained the raw cone penetration test data, whereas the fourth contained the normalized data.

Laboratory Data Analysis

Accuracy of SPT soil types. Table 7-4 shows how the laboratory soil categories compare with the categories from the SPT logs. A careful examination of the table reveals several interesting points. Over 81% of the soil was either a sand or a silty sand, but less than 51% of the samples were identified as such on the SPT logs. Most of the remaining 30% were classified as a clayey sand. Even more enlightening is the fact that only 5 out of 42 silty sand samples were correctly identified, the rest being classified usually as either a sand or a clayey sand. Note also that the 6 samples of silt were generally misclassified as either a clay or clayey sand.

Table 7-4. Accuracy of SPT Soil Types

	<<<<< CATEGORY FROM SPT TEST >>>>>						
USCS CATEGORY	CLAY	SILT	CLAYEY SAND	SILTY SAND	SAND	TOTALS	PERCENT
CLAY	4	0	0	0	0	4	5.8
SILT	2	1	3	0	0	6	8.7
CLAYEY SAND	1	0	2	0	0	3	4.3
SILTY SAND	5	0	15	5	17	42	60.9
SAND	0	0	1	0	13	14	20.3
TOTALS	12	1	21	5	30	69	100.0
PERCENT	17.4	1.4	30.4	7.2	43.5	100.0	

These results would suggest that the drillers have difficulty discriminating silts and silt mixtures, or else a reluctance to use the silt description. The latter is thought likely, since classification from silt categories to others never occurred (i.e., only true silts were called silts, and only true silty sands were called silty sands).

As a result of the laboratory analysis, the SPT logs should be acceptable indicators of soil type, except that true silts are likely to be called clays, and true silty sands are likely to be called either sand or clayey sand (possibly depending on whether the sand or the silt matrix is dominant). These possible misclassifications should be kept in mind when evaluating the results of the discriminant analyses.

Discriminant analysis. Figures 7-5 and 7-6 show the Unified Soil Classification System categories plotted using the raw and normalized ECPT measurements, respectively. Note that using the normalized variables seems to "group" the data a little better. These plots suggest that discriminating clays from clayey sands, and sands from silty sands may prove difficult.

Figures 7-7 and 7-8 show the results of the NEIGHBOR analysis on the laboratory data, using the raw and normalized variables, respectively. Only the region of the plot containing data points is shown because extrapolation may be spurious and misleading. The NEIGHBOR, or nonparametric analysis is very useful as a type of filter for the data. Where the categories overlap (as in the case of the sand and silty sand categories), the NEIGHBOR approach permits identification of the dominant soil type in an area. The two plots did a fairly good job of classifying the soil, accurately predicting the USCS category 50.7% and 49.3% of the time, respectively (Note that the 1.4% difference represents 1 observation). This accuracy rate is likely somewhat biased, however, since the data were used to predict themselves.

The benefits of using the normalized ECPT measurements can be seen in these two figures. In Figure 7-7, the raw measurements result in split categories. Following normalization, the categories group

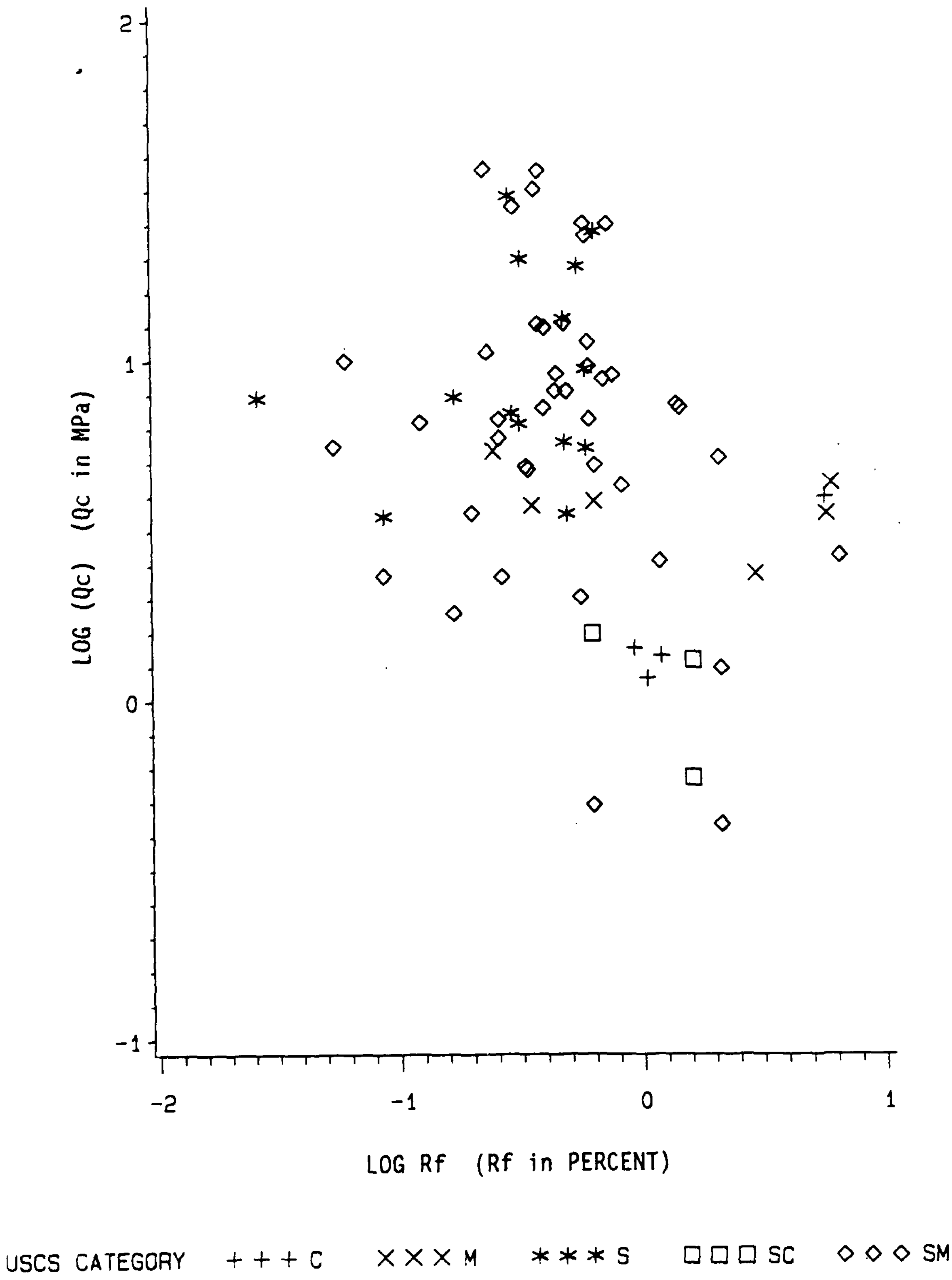


Figure 7-5. Laboratory Classification Data Plotted with ECPT Data

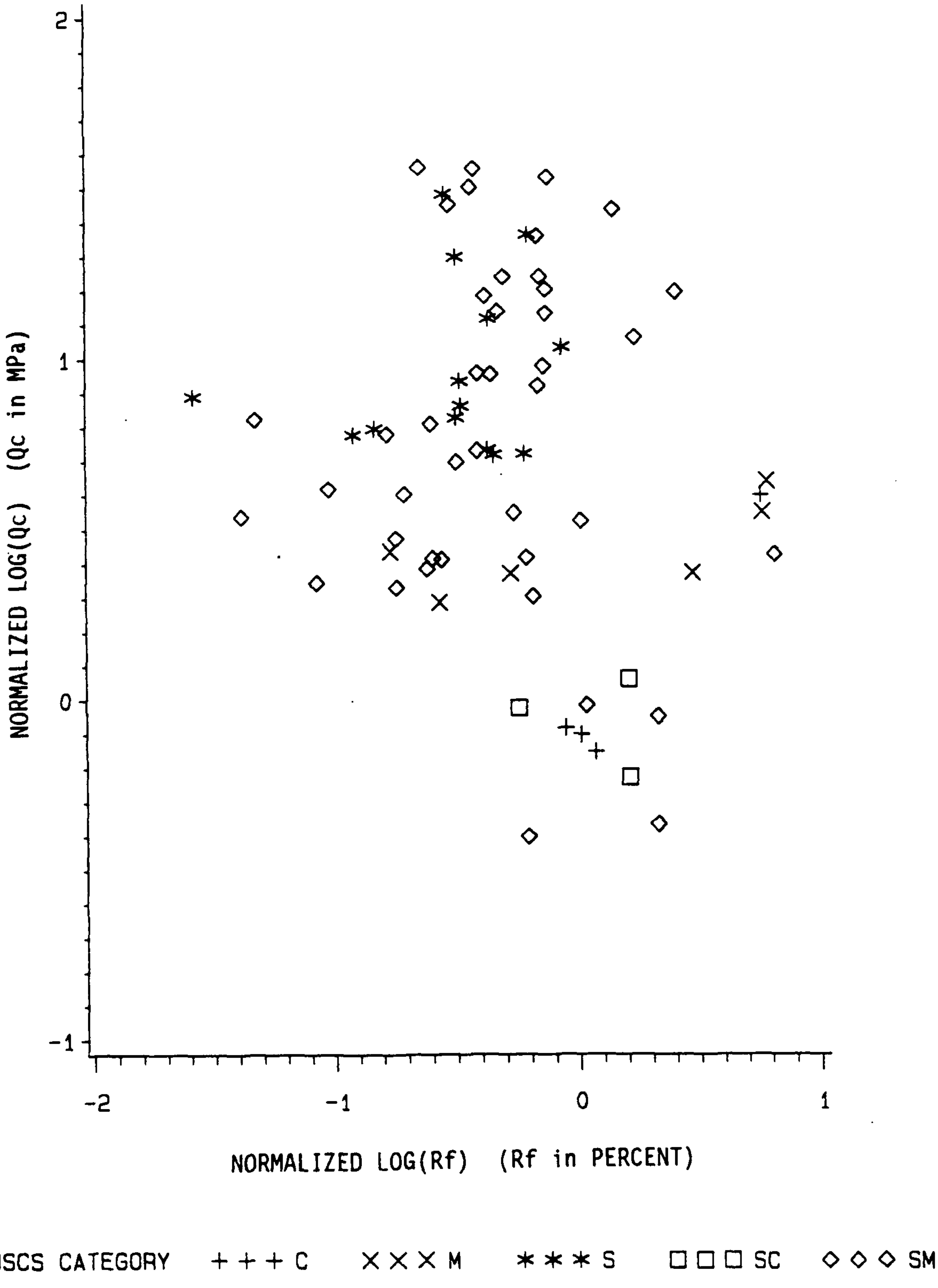


Figure 7-6. Laboratory Classification Data Plotted with ECPT Data Normalized for Overburden

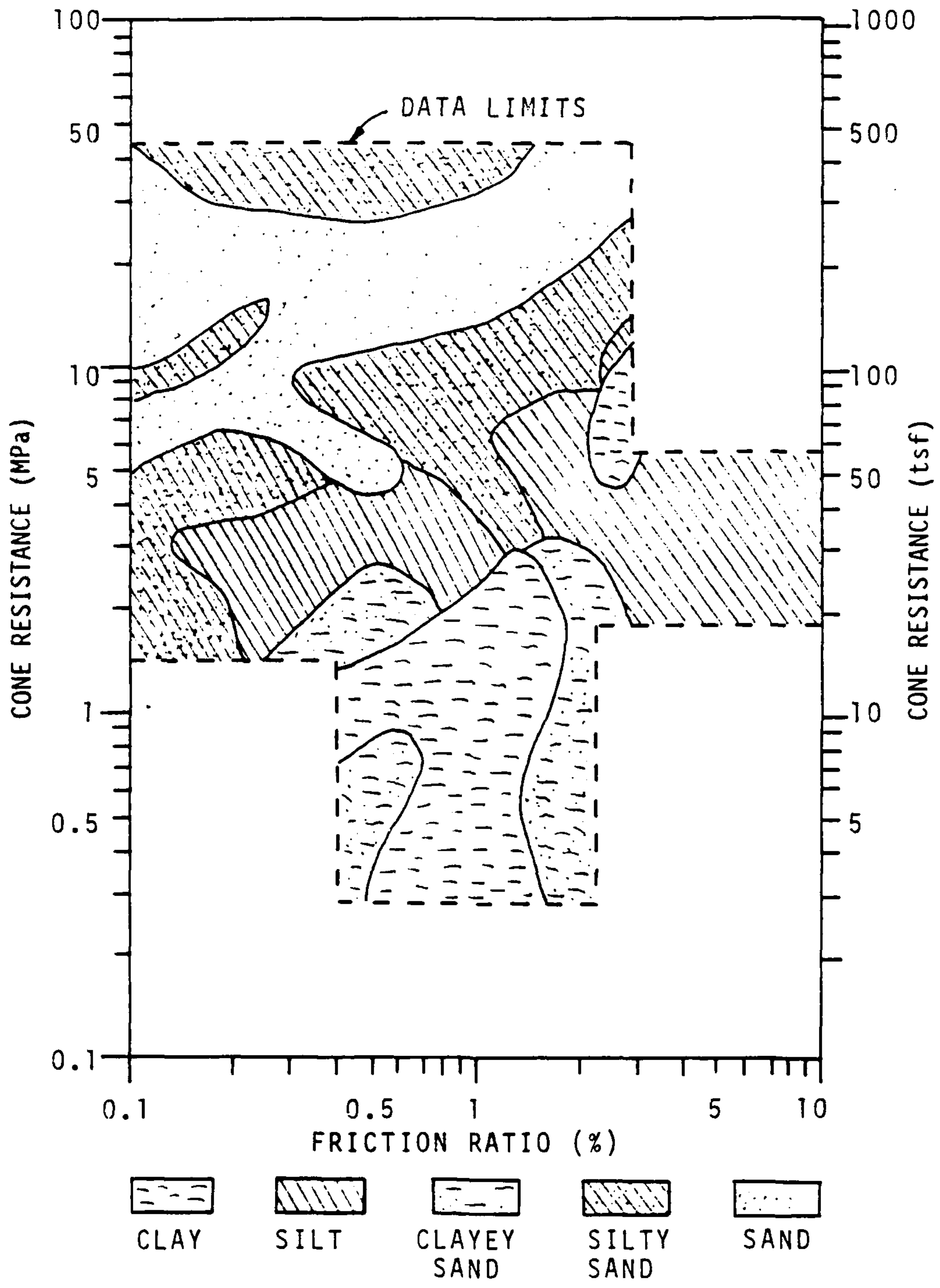


Figure 7-7. Discriminant Analysis of Laboratory Data Using NEIGHBOR Procedure

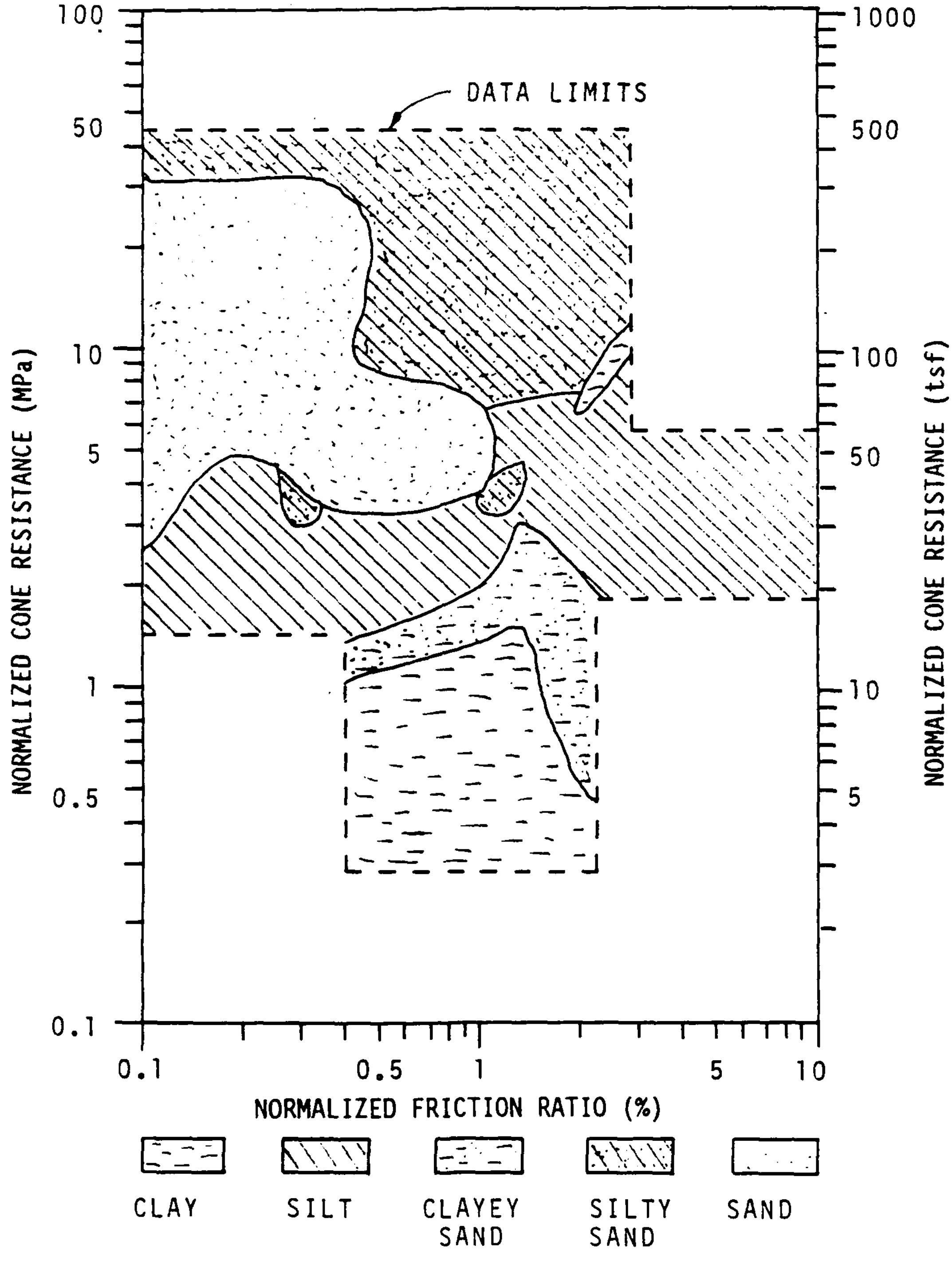


Figure 7-8. Discriminant Analysis Using NEIGHBOR Procedure of Laboratory Data Normalized for Overburden

together better, as seen in Figure 7-8. This grouping of the data should improve classification and result in more confident estimates of the soil types.

The two figures were compared with existing classification charts. Robertson et al. (Figure 7-3) compared favorably with both figures. The other three charts (Figures 7-1, 7-2, and 7-4) all seem to be shifted downward so that clay soils fall in the silt zone, silts in the silty sand zone, and silty sands in the sand zone. The fact that all three charts were shifted similarly is not surprising, since they all have common genealogies.

In order to produce more discrete categories, the DISCRIM procedure (parametric approach) was applied to the raw and normalized data, producing accuracy rates of 40.6 and 42%, respectively. Both graphs were very similar, with the normalized version matching the Robertson et al. chart fairly well. Figure 7-9 shows this graph.

Discriminant Analysis of Field Measurements

The data set used for evaluating electronic cone penetration test measurements for soil identification in Florida consisted of 8087 observations, covering some 7 different soil categories and 15 different soil types. Keeping in mind the significant overlap observed with only 69 observations from the laboratory analysis, the overlap of this large data set can be expected to be intractable. Figure 7-10 shows the general trends of the various soil categories, and is a decent statement of the classification problem. A similar plot of the individual soil types would be even more bewildering.

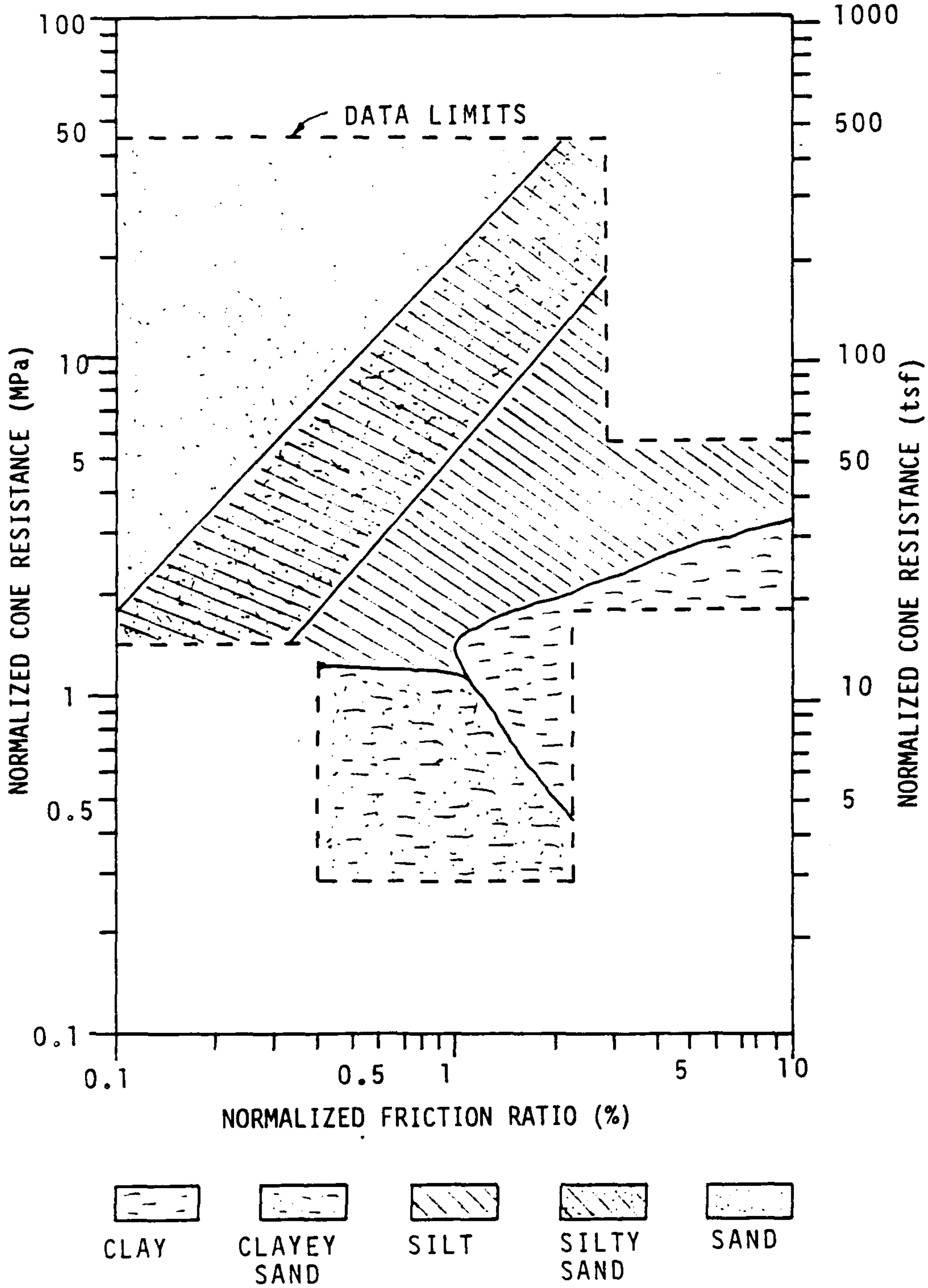


Figure 7-9. Discriminant Analysis Using DISCRIM Procedure of Laboratory Data Normalized for Overburden

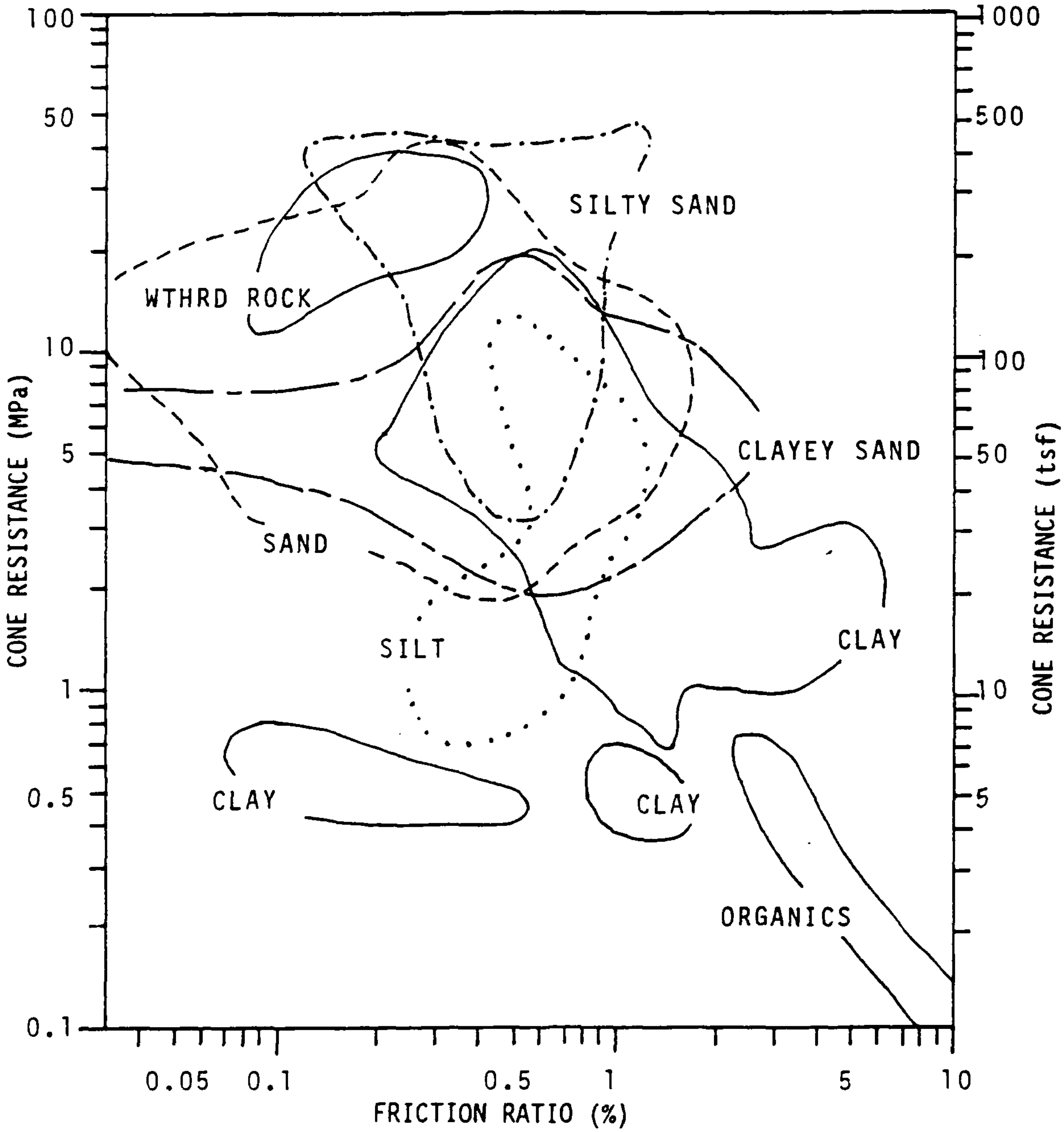


Figure 7-10. General Trends of the Soil Classification Data Set

Before discussing the results of the various discriminant analyses, it is important to remember that the NEIGHBOR approach is best considered a data filter. Disjointed classifications are expected, but this approach allows one to observe the dominant trends without fear that uncontrolled characteristics of the data (such as nonnormal distributions, unequal within-group covariance matrices, and unequal group sizes) will cause spurious and misleading results. The DISCRIM procedure, on the other hand, results in discrete and contiguous classification rules, which are necessary for rational application to other data sets.

Table 7-5 summarizes the accuracy of the various discriminant analyses. Appendix D gives a more detailed breakdown of the results. Note that the DISCRIM procedure did a poor job of accurately predicting individual soil types, averaging only 18% accuracy. The NEIGHBOR approach's better accuracy is artificially high since it is checking itself. This suggests that discrete identification of soil types (sand versus shelly sand, for instance) is not possible with only measurements of q_c and f_s. Classification by category (of which soil types is a subcategory) fares somewhat better, with the DISCRIM approach averaging approximately 40% accuracy. The column labeled "GROUP" is the same as "CATEGORY," except that the sand, silty sand, and clayey sand categories have been combined into a single category. The DISCRIM approach averaged approximately 70% accuracy by group. This significant improvement reflects the failure of the cone to discriminate between the various types of sands. This result is not surprising, as seen by the significant overlap of categories in Figures 7-5 and 7-10.

Table 7-5. Accuracy of Discriminant Analysis Approaches

DATA SOURCE	METHOD	NORMALIZED	CLASS VARIABLE	SOIL TYPE (%)	CATEGORY (%)	GROUP (%)
LAB	DISCRIM	NO	USCSCAT		42.0	76.8
		YES	USCSCAT		40.6	79.7
	NEIGHBOR	NO	USCSCAT		50.7	73.9
		YES	USCSCAT		49.3	73.9
FIELD	DISCRIM	NO	SOILTYPE	19.3	32.4	56.9
		YES	SOILTYPE	17.4	42.4	66.9
		NO	CATEGORY		39.4	69.1
		YES	CATEGORY		44.1	71.0
	NEIGHBOR	NO	SOILTYPE	52.5	62.1	87.1
		YES	SOILTYPE	55.5	65.7	87.1
		NO	CATEGORY		64.1	86.5
		YES	CATEGORY		66.5	85.9

Table 7-5 shows that the average improvement in the accuracy rate due to normalizing the data following Olsen and Malone's method is 2.4%. Of even more interest is the nature of the spread. Normalizing the data reduced accuracy at most 1.9% in 4 comparisons, had no effect in 2 comparisons, and improved accuracy as much as 10% in 8 comparisons. Thus it would seem that normalizing the data is helpful, often significantly so. This improvement is likely due to the improved clustering of the data by soil type after it has been normalized. Thus, while the use of normalized variables may not result in dramatic improvement in classification accuracy, the benefits are significant enough to warrant their use.

Figures 7-11 and 7-12 show the results of using the DISCRIM and the NEIGHBOR approaches, respectively, on the normalized data classified by category. In comparing the two figures, it is apparent that the smallest groups are occupying a disproportionate share of the DISCRIM graph, at the likely expense of the sand and clay categories. Despite some disjointedness, the NEIGHBOR approach has done a good job of identifying quasi-contiguous classification regions. Thus while the results of the parametric approach are not bad, the nonparametric approach will be used for evaluating existing classification schemes. This is a good result, since no assumptions on the data distribution need to be made to use the nonparametric approach, making any conclusions on the data "safer."

When Figure 7-12 is compared with existing classification charts, the Robertson et al. chart seems to fit best. The major differences are that the organic material intrudes into the clay region a bit too much, the clayey sands fall mainly in the silt and silty sand region, and the sands and silty sands are mixed together. Interestingly enough, the latter two could have been predicted based on the results of the laboratory analyses. The clayey sands are likely silty sands that have been misclassified on the SPT logs, and the sands and silty sands have already been observed to overlap considerably.

Recommended Classification Scheme

The use of ECPT measurements normalized to an overburden pressure of 96 kPa (1 tsf) is recommended, as accuracy can be enhanced as much as 10% over the use of no normalization. Normalization can be implemented using Olsen and Malone's approach (36), as applied in Appendix E.

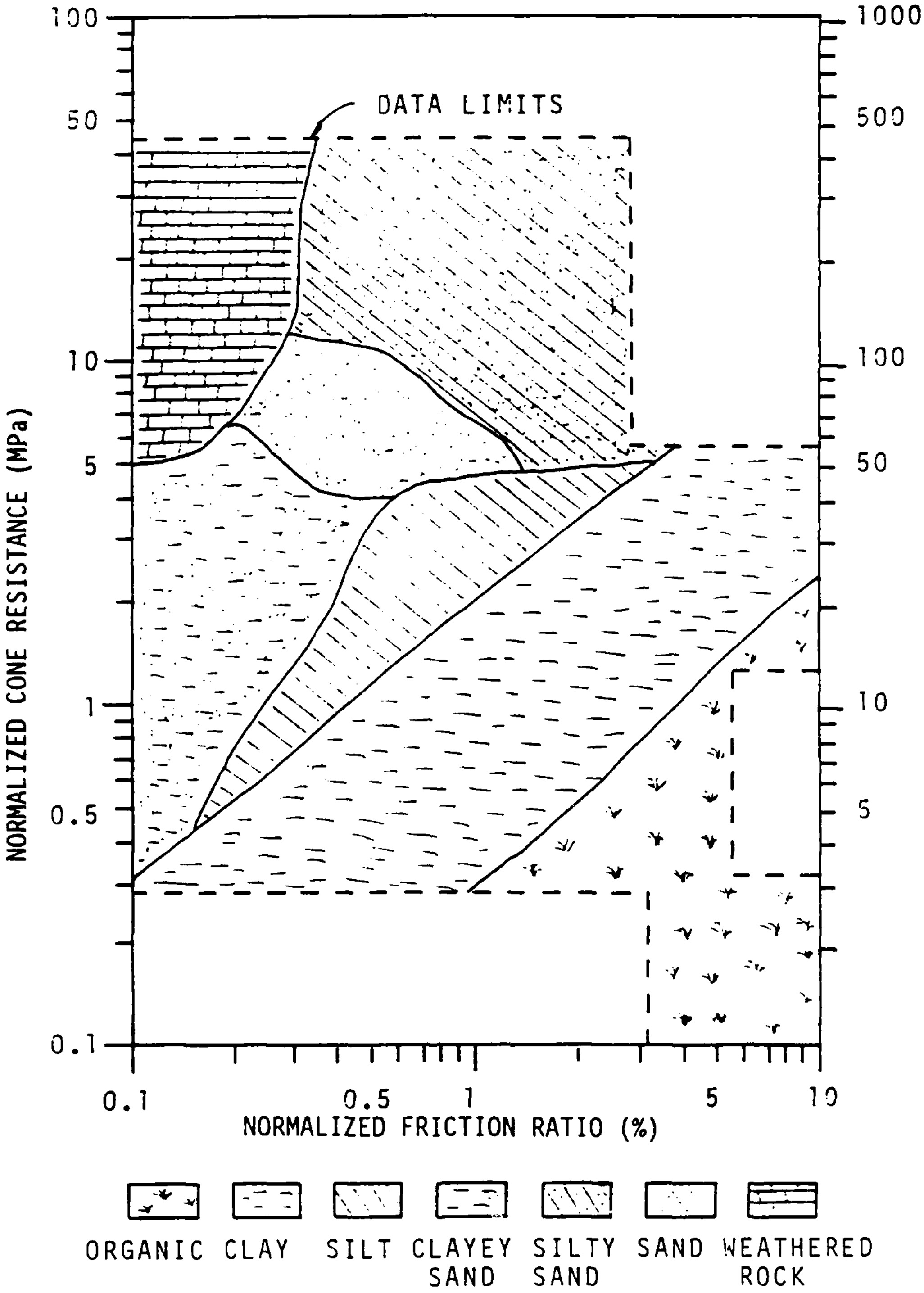


Figure 7-11. DISCRIM Discriminant Analysis on Data Classified by Category

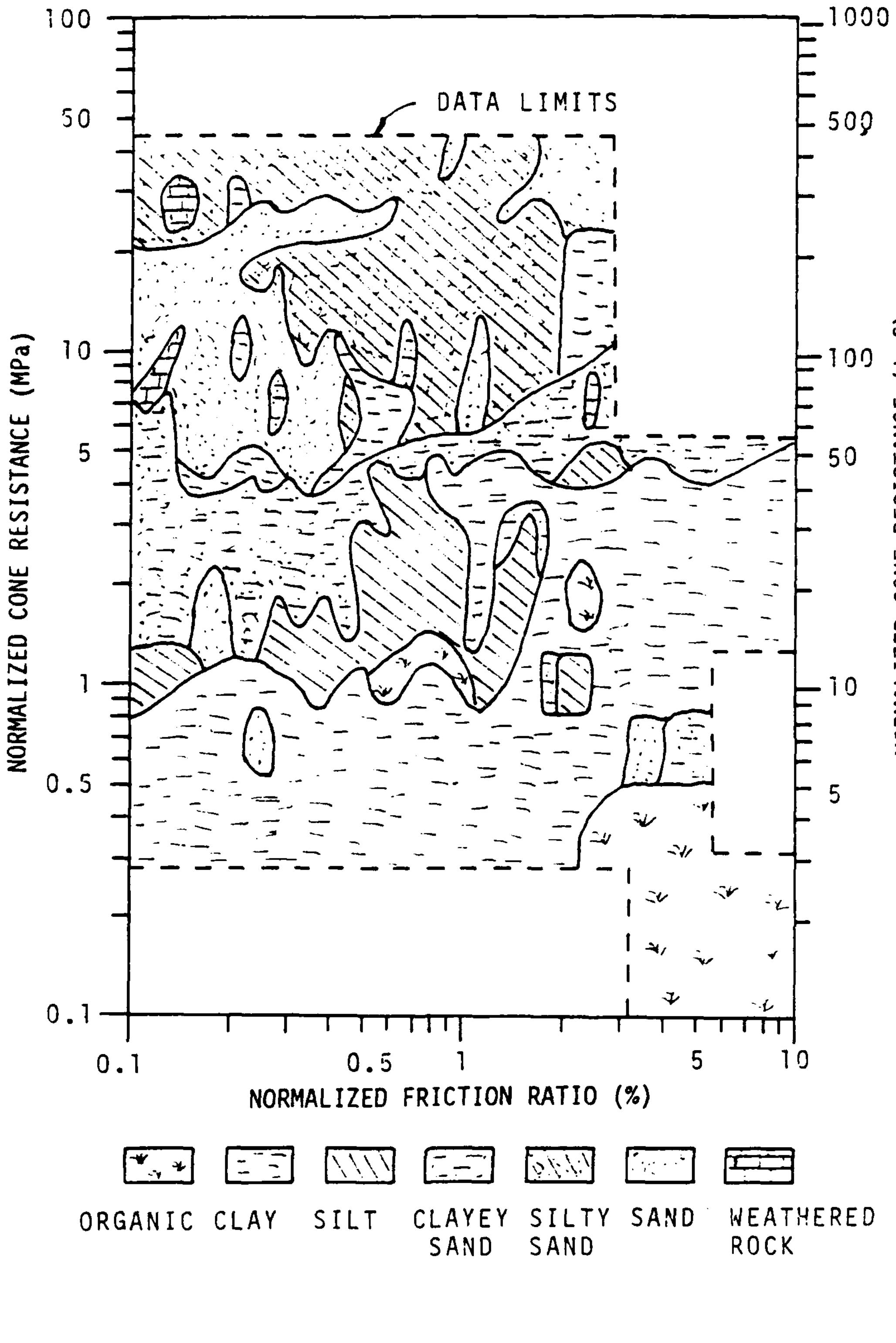


Figure 7-12. NEIGHBOR Discriminant Analysis on Data Classified by Category

Based on a careful study of the various existing classification schemes, the Robertson et al. chart seems the closest to describing indigenous Florida soils. A few changes are recommended which may better reflect the results of this study. No changes will be made outside of the range of the data collected for this study. If soils falling in these areas are encountered, their analysis can be left to future research.

Figure 7-13 shows the modified Robertson et al. chart. The major differences are:

--The category designations have been modified to more closely represent the Unified Soil Classification System designation. Also, the "clay" and the "silty clay to clay" regions of the Robertson et al. chart have been combined into a single "clay" region. The "sensitive fine grained" zone has been renamed "clay and sensitive fine grained" since clays have been identified at least in the upper portion of this zone.

--The sand and silty sand areas have been vertically divided, as opposed to the horizontal division of Robertson et al., to better reflect the findings of this study.

--The organic material area has been moved slightly into the clay area.

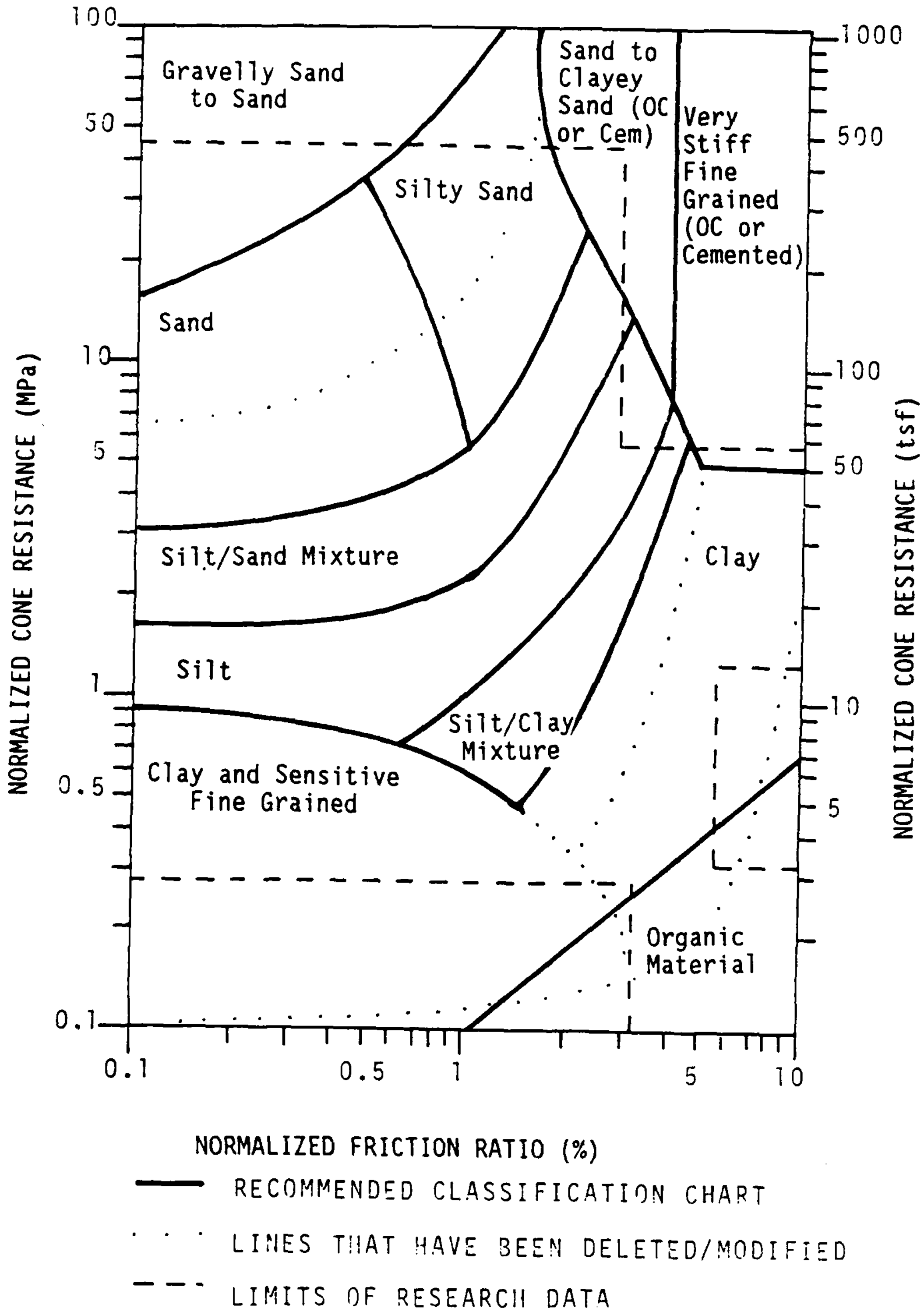


Figure 7-13. Recommended ECPT Soil Classification Chart for Florida Soils

CHAPTER 8
SPT-ECPT CORRELATIONS FOR FLORIDA SOILS

Introduction

The standard penetration test (SPT) is the most common in situ test in North America, providing the field data for as much as 90% of the conventional foundation design (45). As a result a considerable body of experience with the SPT has developed, despite the numerous objections to the test that were discussed in Chapter 7. To take advantage of this body of experience, correlations between cone penetration test measurements and the SPT N-value are desirable.

Numerous past studies relating q_c and N have been undertaken, leading to much confusion due to conflicting results. For fine sands Meyerhof in 1956 proposed (34)

$$q_c = 0.4\ N \quad \text{(8-1)}$$

with q_c in MPa (for q_c in tsf, multiply the constant by 10.45). Abdrabbo and Mahmoud found this value to be double their measured value in Egyptian medium sands, recommending a constant of 0.2 instead (1). Peck et al. estimated the constant to be 0.19 for silts and sand/silt/clay mixtures, 0.29-0.38 for fine sands to medium sands, and 0.48-0.57 for coarse sands (38). Meigh and Nixon showed the ratio to range between 0.25 for silty fine sands up to 1.2+ for coarse gravels (34). In 1983 Robertson et al. developed a chart relating q_c/N with mean grain size, and was published by Seed and De Alba as shown in Figure 8-1 (52).

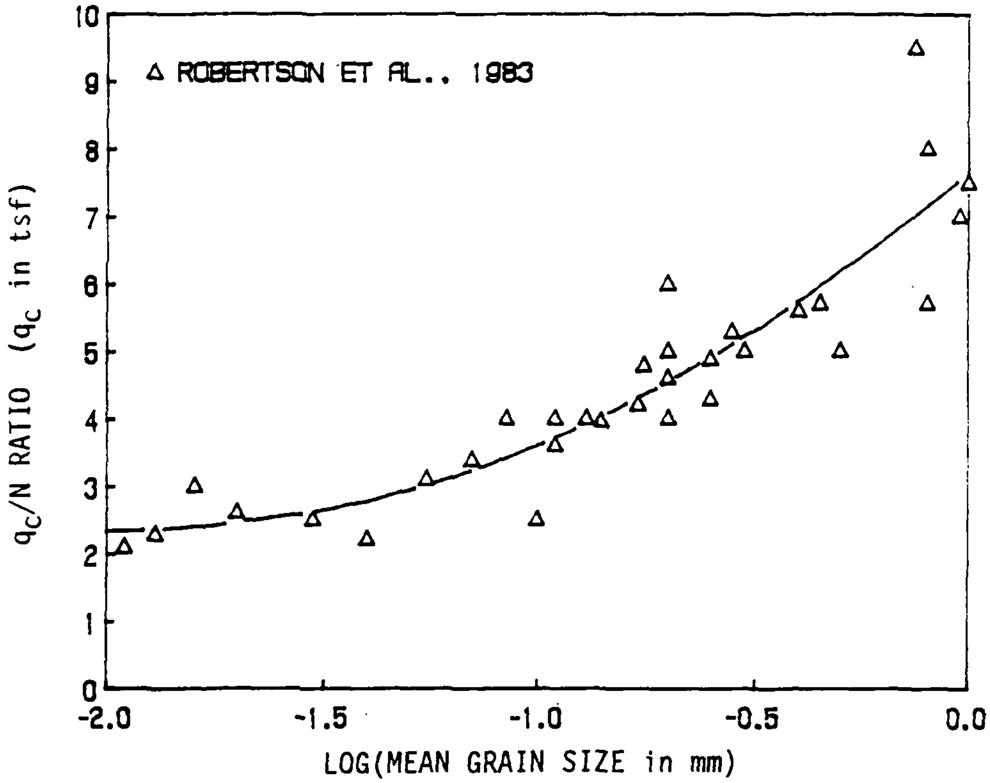


Figure 8-1. Variation of q_c/N Ratio with Mean Grain Size (after Seed and De Alba, (52)) (Used with permission of ASCE)

The purpose of this phase of the research is to evaluate the relationship between the SPT N-value and the ECPT measurements, and to recommend suitable correlations for Florida soils. To accomplish this objective a data base was established containing measurements from some 20 pairs of SPT and ECPT soundings in close proximity to one another. These data were then evaluated using exploratory data analysis and regression analysis to determine the relationships.

SPT-ECPT Data Base

A large data base was created to evaluate the use of the electronic cone penetration test for estimating SPT N-values in Florida soils. The basic approach was to collect ECPT data near available SPTs. The same data base used in the classification analysis (Chapter 7) was used here, except that a more stringent distance criteria was employed to better insure that the two soundings were in nearly identical soils from the standpoint of strength (and not simply the same "type" of soil). A maximum separation distance of 6.1 m (20 ft) was selected, and a minimum separation of 1.2 m (4 ft) was used to minimize radial stress relief in the boreholes, as recommended by Robertson and Campanella (41). This data base represented 20 soundings in 7 Florida cities. Table 8-1 summarizes the data base. A more detailed summary is in Appendix A and Knox (25).

The ECPT data were filtered using the average-value filter presented in Chapter 3. This was felt to be appropriate since the N-value represents an average blow count over a 0.3 m (1 ft) increment. The filtered data were then merged with the corresponding SPT N-value, producing 606 observations.

In addition to the raw cone penetration test measurements, ECPT measurements normalized to an effective overburden pressure of 96 kPa (1 tsf) were calculated, using Olsen and Malone's approach as discussed in Chapter 7 and Appendix E (36). An effective overburden correction was also determined for the SPT N-value, using the following equation from Peck, Hanson, and Thornburn (38):

$$N_{corr} = [0.77 \log_{10}(20/p'_v)]\ N \quad \text{(8-2)}$$

Table 8-1. SPT-ECPT Data Base

SITE	ECPT #	SPT #	ECPT-SPT DISTANCE
Fort Myers Interchange	C010D	S010A	4.8 m (16 ft)
West Palm I-95	C015A	S015A	4.5 m (15 ft)
	C017B	S017A	4.5 m (15 ft)
Choctawhatchee Bay	C019B	S019A	1.2 m (4 ft)
	C019G	S019C	5.2 m (17 ft)
	C019J	S019B	4.4 m (14 ft)
	C019K	S019B	5.0 m (16 ft)
	C020B	S020A	1.5 m (5 ft)
	C021D	S021A	4.7 m (15 ft)
White City	C022A	S022A	7.6 m (25 ft)
	C022B	S022B	1.6 m (5 ft)
	C022C	S022C	3.0 m (10 ft)
Orlando Arena	C023D	S023E	1.5 m (5 ft)
Orlando Hotel	C024A	S024A	2.2 m (7.4 ft)
	C024B	S024B	3.1 m (10 ft)
	C026A	S026A	4.3 m (14 ft)
Jacksonville Coal Terminal	C028B	S028A	See Note
West Bay	C030A	S030A	2.7 m (9 ft)
	C030D	S030D	2.9 m (10 ft)
	C030F	S030F	5.6 m (18 ft)

Note: Exact location of Jacksonville SPT undetermined, but believe distance criteria met. Inspection of data supports belief that soils were correctly identified.

where N_{corr} is the corrected N-value, and p_v' is the effective overburden pressure. An average total unit weight of 17.3 kN/m^3 (110 pcf) was assumed for the soil.

Data Analysis

Exploratory Data Analysis

Exploratory data analysis using the SAS procedure UNIVARIATE was initially performed to examine the data, which were grouped by soil category (organics, clay, silt, clayey sand, silty sand, sand, and rock). Of particular interest were the SPT N-values and the q_c/N ratios, including the nature of their distributions. If the distributions were not normally-distributed, then estimates of the mean and regression analyses would likely not reflect the majority of the data. Inspection of the data showed the ratios to be approximately log-normally distributed, with a logarithmic transformation proving effective in achieving a more symmetric frequency distribution. Table 8-2 summarizes the results of the exploratory analysis on the q_c/N ratios, calculated using both "raw" measurements, and using ECPT and SPT measurements corrected for effective overburden pressure. The means were determined using logarithmically-transformed variables.

Figure 8-2 compares the results of the exploratory data analysis with Figure 8-1. The mean grain size, D_{50}, was estimated using Robertson et al. (45) combined with guidance from Lee et al. (29). The figure shows the mean value (the hatch mark) plus or minus one standard deviation (the range of the standard deviation is unbalanced as a result of the conversion back from a transformed data set). Note that the average q_c/N ratios from this study are significantly higher than the

Table 8-2. Exploratory Data Analysis of q_c/N Ratios

SOIL CATEGORY	NUMBER OF OBSERVATIONS	MEAN Qc/N (Qc in MPa/tsf)	NORMALIZED MEAN Qc/N (Qc in MPa/tsf)
CLAY	72	0.46/4.77	0.39/4.04
SILT	16	0.26/2.75	0.29/3.07
CLAYEY SAND	114	0.53/5.51	0.43/4.47
SILTY SAND	97	0.55/5.72	0.59/6.15
SAND	303	0.68/7.10	0.71/7.41
ROCK (WEATHERED)	5	0.70/7.28	0.73/7.64

literature would suggest. Also, the scatter in the data was considerable. The wide scatter in the data could possibly reflect the problem of repeatability with the standard penetration test, as discussed in Chapter 7. Since most of the data came from near-coastal sites, the higher-than-expected values may also reflect possible cementation in the soil. It is thought that such cementation would significantly affect q_c since the penetrometer tip is "pushed" into the ground, whereas the SPT N-value may be much less affected since the split-barrel sampler is "driven," potentially breaking down the cementation. Liquifaction of loose sands during SPT driving is also thought to possibly contribute to low N-values relative to the cone. Further research is warranted. If the data do indeed reflect cementation, then the combination of the SPT and the ECPT may be effective in aiding identification of cemented soils.

Regression Analysis

Most past research has determined q_c-N relationships based on soil type. Since soil type can be estimated from knowledge of the cone

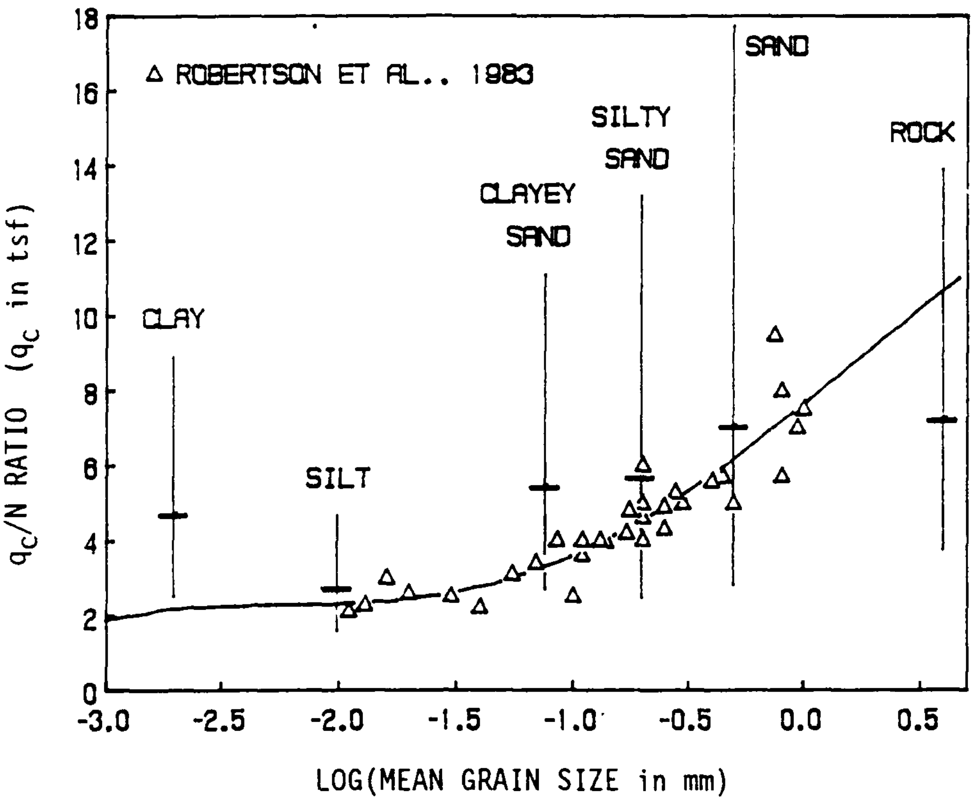


Figure 8-2. Results of q_c/N Ratio Study

resistance and friction ratio, a relationship between these ECPT measurements and N was sought using linear regression analysis. The variables were logarithmically-transformed to improve their regression behavior, and both normalized and nonnormalized measurements were evaluated. The regression model used was

$$\log_{10}(N) = a_0 + a_1\log(q_c) + a_2\log(R_f) \quad \text{(8-3)}$$

where q_c is in MPa. Table 8-3 summarizes the results of the analysis.

Table 8-3 demonstrates that the friction ratio has a negligible effect on the squared multiple correlation coefficient, R^2, and can safely be omitted. This finding suggests that previous q_c/N research detecting differences in soil types was possibly detecting differences

Table 8-3. Results of SPT-ECPT Regression Analysis

INDEPENDENT VARIABLES	NORMALIZED	a(0)	a(1)	a(2)	R^2	RMSE
$\log(q_c)$	NO	0.535	0.631		0.38	0.33
	YES	0.628	0.500		0.33	0.34
$\log(q_c)$, $\log(R_f)$	NO	0.554	0.662	0.126	0.39	0.33
	YES	0.622	0.498	-0.018	0.33	0.34

in the range of the q_c value, since a certain soil type tends to occupy a given range of q_c values. Correspondingly, friction resistance measurements tell little or nothing about predicted N-values.

Table 8-3 also suggests that normalizing the data has a negative impact on the results. Since both the SPT and ECPT tests are subjected to the same effective overburden pressure, additional "correction" apparently only contributes to the data scatter in determining correlations.

Based on the results of the regression analysis, the SPT-ECPT .mb6 correlation was found to be

$N = 3.43\ q_c^{0.631}$ (q_c in MPa) ....(8-4)

$N = 0.781\ q_c^{0.631}$ (q_c in tsf) ....(8-5)

This relationship, of course, will result in lower estimates of N than would be expected from the literature as a result of the high q_c/N ratios in the data base, as discussed above. While the exact correlation between cone resistance and SPT N-value may be open to question, the findings related to the effect of soil type and normalizing data are thought valid. The approach to analyzing SPT-ECPT data presented herein should be a suitable model for future research.

In evaluating the significance of the regression analysis, the R^2 values in Table 8-3 are admittedly not very high. However, given the problems with replicating SPT data, low correlation coefficients can be expected. Table 8-4 shows that the root mean square error of the regression analysis, which is an estimate of the standard deviation of the dependent variable (log(N)), compares very favorably with the standard deviation of log(N). This is further evidence that grouping data by soil types is not the best approach when attempting to determine an SPT-ECPT correlation.

Table 8-4. Descriptive Statistics for log(N) in Units of log(blows/ft)

SOIL CATEGORY	NUMBER OF OBSERVATIONS	MEAN	STANDARD DEVIATION
CLAY	72	0.68	0.34
SILT	16	0.85	0.02*
CLAYEY SAND	114	0.99	0.34
SILTY SAND	97	1.34	0.37
SAND	303	1.07	0.42
ROCK (WEATHERED)	5	1.46	0.17*

* The low standard deviation is due to a relatively small number of contiguous measurements.

CHAPTER 9
CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

Summary and Conclusions

1. The main objective of this research was to evaluate techniques to improve the application of in situ penetration testing to Florida soils, with emphasis on the electronic cone penetration test (ECPT). Specifically, the analysis covered evaluation of spatial variability, classification of soils using the ECPT, and ECPT correlations with the standard penetration test (SPT).

2. The ECPT is a relatively fast and inexpensive test for characterizing geotechnical conditions at a site. The test is best used to obtain cone resistance measurements (q_c), which are reliable and reproducible measures of soil strength. The design of the subtraction-type cone makes friction resistance measurements (f_s) less dependable, particularly in weak soils.

3. Two data manipulation techniques were used to improve the response of the data to statistical analyses, and are recommended for future work. The first involved a logarithmic (base 10) transformation which improved the symmetry of the data by spreading out low-magnitude values and contracting high-magnitude ones. A side benefit was the elimination of negative values which occasionally result from regression analyses. The second technique used an average-value filter to smooth out high-frequency spikes in the ECPT data. This simple filter reduced the data

scatter on the order of 15-20%, while reducing the number of data points by a factor of 10. This reduction in the number of data points can greatly reduce computer analysis time and hardware requirements. The filter is recommended in applications where the general trend of the soil is the major item of interest.

4. The term "local variability" was adopted to describe the point-to-point variability of a measured soil property, encompassing measurement errors, signal noise, and the innate randomness of soil. The magnitude of this local variability was estimated for the UF friction-cone penetrometers using regression techniques. It proved to be a dominant portion of the variability observed at the two sites in the spatial variability study employing the ECPT.

5. Several approaches to quantifying the spatial variability of soil were compared. The deterministic or single-value approaches involved using the mean, median, and 10% trimmed average to describe a soil property at a site. The three descriptive statistics were generally inferior to the other more sophisticated approaches in ability to predict soil properties.

6. Four distance-weighting methods for handling spatial variability were evaluated: linear interpolation, two weight functions based on reciprocal distances, and a random field model. The random field model was a hybrid model, describing a site's general trends using regression analysis, and its local trends using a weight function based on an estimated autocorrelation function. The four distance-weighting methods were fairly alike in their ability to handle spatial variability and interpolate between soundings. As a group they were slightly inferior

on the average to the regression techniques, and the scatter in the results was somewhat higher because these methods are significantly influenced by individual soundings.

7. Regression analysis using various regression models proved most useful for describing the variability of soil properties at a site. The average error from regression was lower than the other prediction methods tested, and the scatter in the average error tended to be less. This reduction in the variability of the error is attributed to the fact that individual soundings have less impact on the "average" value predicted by the regression. The regression model should have an adequate number of terms to describe the general trends, generally up to order 2 horizontally and order 2 to 5 or more vertically. The use of a stepwise regression analysis to generate a suitable model proved useful.

8. The root mean square error (RMSE) obtained from regression analysis generally estimated the measured error in a prediction within 25%. Knowledge of the estimated RMSE, coupled with knowledge of the local variability associated with the in situ test in question, would prove useful in evaluating a site investigation program and determining whether additional soundings are needed.

9. A comparison of SPT soil descriptions with laboratory classification using the Unified Soil Classification System showed that the SPT logs did not identify silts and silt mixtures well. The silts tended to be identified as clays, and silty sands were identified as either sands or clayey sands.

10. Normalizing ECPT data to an overburden pressure of 96 kPa (1 tsf) enhanced the classification of soil by tending to "group" like soils together. The method of normalization is based on Olsen and Malone (36), and has been adapted for the computer.

11. The results of the discriminant analysis of ECPT data to classify soils (classified by SPT soil descriptions) showed that the cone can accurately place soil into general categories approximately 40% of the time. The general categories were organics, clays, silts, clayey sands, silty sands, sands, and weathered rock. If the clayey sands, silty sands, and sands are grouped into a single sand category, the accuracy improves to approximately 70%. This significant improvement probably reflects the difficulty the SPT drillers have in accurately describing mixed sand/silt soils, as discussed above. A slightly modified Robertson et al. (44) classification chart using normalized ECPT data is recommended for use in Florida.

12. The SPT-ECPT correlation study produced some unexpected findings. Average q_c/N ratios for the Florida soils were much higher than expected based on a review of the literature. Possible explanations include the poor repeatability of the SPT test in general, the possibility (or probability) of cemented soils, and possible liquefaction of sands during SPT driving. Regression analysis of the data suggested that the nature of the SPT-ECPT relationship is more a function of the magnitude of the cone resistance, and less of the actual soil type. Normalization of the data for overburden pressure proved detrimental to the correlation.

Recommendations for Future Research

1. An improved electronic friction-cone penetrometer tip is needed to accurately measure soil strength ranging from weak to strong. The subtraction-type penetrometer tip, while a robust design, lacks the sensitivity required for measuring friction resistance in weak soils. A sturdy tip which can measure the friction directly, and not by subtracting two large numbers from one another is required. To avoid the problems associated with dirt and water ingress into the electronics of the tip, an unitized design would be desirable. A starting point for this effort could be the evaluation of the University of Florida 15-ton penetrometer tip to determine the source of the apparently poor friction resistance readings.

2. Expansion and use of the Florida in situ testing data base should continue. A wealth of information is available by simply collecting and coding data available from contractors and government agencies, however use of these data is complicated by the fact that their purposes in running the tests do not often coincide with the needs of research. An even greater return on efforts expended could be realized by careful design of the research program a priori, and coordination with the testing agencies prior to and throughout the testing program. Such coordination will prove difficult, however, due to the industry's emphasis on productivity and economy.

3. Additional work on spatial variability is required, with emphasis on some type of random field model due to its basis in stochastic theory, and the attractiveness of a hybrid model which considers both general site trends and local deviations to the trend. In particular,

10. Normalizing ECPT data to an overburden pressure of 96 kPa (1 tsf) enhanced the classification of soil by tending to "group" like soils together. The method of normalization is based on Olsen and Malone (36), and has been adapted for the computer.

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additional study into horizontal autocorrelation seems warranted to better quantify the lag distances, which are now believed to be fairly small (tens of feet, maybe, as opposed to hundreds of feet). A testing program consisting of relatively closely spaced soundings, perhaps in a grid pattern, would permit more reliable estimation of the autocorrelation function. Such a grid pattern would also permit estimation of the testing device's local variability, which is likely to represent a significant part of the total variability in a site.

4. Expansion of the laboratory data base for classification using the ECPT is required. While the SPT soil descriptions are not bad, they must be supplemented with verifiable data to withstand scrutiny.

5. Investigation into the use of pore pressure measurements for soil identification and soil property correlations should be undertaken. Such a study should also investigate materials, equipment, and procedures to reliably and easily obtain interpretable pore pressure measurements. The present approach of saturating the porous filter elements by boiling and under vacuum are too cumbersome and uncertain for field use. Also troublesome are the problems associated with maintaining saturation above the water table.

6. Additional study into the SPT-ECPT correlations is required. Such a study should better control the SPT tests to insure consistency and reliability of these data (as much as is possible with the SPT test). Also, attempts to obtain truly undisturbed soil samples would help shed some light on questions relating to possible cementation or liquefaction effects. Again, a grid pattern of alternating SPTs and ECPTs would be useful in statistically analyzing the data.

7. Comparisons between electronic and mechanical cone penetration tests should be made to evaluate whether or not the two devices make equivalent measurements of q_c and f_s. The existing data base may already contain the data required for such a study.

8. The effects of pile driving on ECPT measurements is another possible research topic. Presently, only the Sarasota Garage site and the Choctawhatchee Bay site contain penetrometer soundings taken before and after pile driving. The White City site may be available in the near future for "after" soundings. Since such a study would not necessarily require pile load tests, additional field testing may also be accomplished by coordination with a cooperative pile driving contractor.

9. The literature should be searched for information relating ECPT measurements (or penetration testing in general) with the soil property inputs to the University of Florida's axially-loaded pile capacity program, TZD (i.e., maximum shear stress, initial shear modulus, Poisson's ratio, ultimate pile point resistance, and pile-soil interaction effects). The pile load tests and the ECPTs in the data base could then be used with TZD to evaluate which of the ECPT-soil property relationships are best able to predict pile load-deformation behavior.

APPENDIX A
INDEX TO IN SITU TEST DATA BASE

LAST UPDATE: 3 MAY 1989

NOTE: This index is designed to aid in locating and identifying information available in the Pile Project Files at the University of Florida. Missing information may not be available, or may simply be awaiting input.

LEGEND:
GSE - GROUND SURFACE ELEVATION
GWT - EST. WATER TABLE (Elevation unless noted otherwise)
TIP IN - PILE IS TIPPED IN (sand, clay, etc.)
TIP EL - PILE TIP ELEVATION
TYPE - TYPE OF PILE
- PS - PRESTRESSED
- PC - PRECAST
- S - STEEL
- C - CONCRETE
- V - VOIDED
- RD - ROUND
- SQ - SQUARE

ti - TIPPED IN
pp - PORE PRESSURE
red - FRICTION READING NOT USABLE
yellow - FRICTION READING BORDERLINE
SOILS:
- S - SAND
- M - SILT
- C - CLAY
- CS - SANDY CLAY
- SM - SILTY SAND
- etc.

FILES:
- Prefix P - PILE LOAD TEST
  - E - ELECTRONIC CONE PENETRATION TEST
  - M - MECHANICAL CONE PENETRATION TEST
  - S - STANDARD PENETRATION TEST (BLOW COUNTS)
  - B - BORING LOGS (FROM SPT)
- Number - SITE IDENTIFICATION NUMBER
- SUFFIX A - FIRST TEST OF SERIES
  - B - SECOND TEST OF SERIES, ETC.

CONTENTS:	SITE #: 001	SITE:	APALACHICOLA RIVER BRIDGE-PIER 3 CLAYEY SAND, ti DENSE CLAYEY SAND
	SITE #: 002	SITE:	APALACHICOLA RIVER BRIDGE-BENT 16 SANDY CLAY, ti CLAYEY SAND
	SITE #: 003	SITE:	APALACHICOLA BAY BRIDGE-BENT 22 CLAY, ti V.STIFF SANDY CLAY W/SHELL
	SITE #: 004	SITE:	OVERSTREET BRIDGE-PIER 11 SAND & CLAY, ti SHELLY SAND
	SITE #: 005	SITE:	OVERSTREET BRIDGE-PIER 16 SAND & CLAY, ti CLAYEY SAND & SHELL
	SITE #: 006	SITE:	SARASOTA GARAGE-SP7 SAND, ti LIMEROCK
	SITE #: 007	SITE:	SARASOTA GARAGE-SP5 SAND, ti LIMEROCK (probably)
	SITE #: 008	SITE:	SARASOTA CONDO SAND & CLAYEY SAND, ti LIMEROCK
	SITE #: 009	SITE:	SARASOTA - MANATEE LANDFILL SAND & CLAY, ***NO PLT***
	SITE #: 010	SITE:	FT MYERS - CONCRETE PILE probably CLAY, ti CLAY
	SITE #: 011	SITE:	FT MYERS - STEEL PILE probably CLAY, ti CEMENTED SHELL
	SITE #: 012	SITE:	FT MYERS - AIRPORT probably MARINE CLAYS, ***NO PLT***
	SITE #: 013	SITE:	PORT ORANGE BENT 19 SHELLY SAND, ti SHELLY SAND
	SITE #: 014	SITE:	PORT ORANGE BENT 2 SHELLY SAND, ti SHELLY SAND
	SITE #: 015	SITE:	WEST PALM I-95 PIER B-4 SAND, ti SAND w/tr SHELL
	SITE #: 016	SITE:	WEST PALM I-95 PIER B-6 SAND w/tr SHELL, ti SAND w/tr SHELL
	SITE #: 017	SITE:	WEST PALM I-95 PIER B-9 SAND w/tr SHELL, ti SAND w/tr SHELL
	SITE #: 018	SITE:	WEST PALM I-95 PIER C-2 SAND & SHELLY SAND, ti SHELLY SAND
	SITE #: 019	SITE:	CHOCTAWHATCHEE BAY PIER 1 SAND & SILTY SAND, ti SAND
	SITE #: 020	SITE:	CHOCTAWHATCHEE BAY PIER 4 SAND, SOME CLAY, ti SAND
	SITE #: 021	SITE:	CHOCTAWHATCHEE BAY FSB 26 probably SAND, SOME CLAY, ti SAND
	SITE #: 022	SITE:	WHITE CITY probably SAND, SOME CLAY
	SITE #: 023	SITE:	ORLANDO ARENA SAND ON CLAYEY SAND, ti CLAYEY SAND
	SITE #: 024	SITE:	ORLANDO HOTEL SOUTH ALTERNATING S & SC, ti SC w/SHELL
	SITE #: 025	SITE:	ORLANDO HOTEL NORTH ALTERNATING S & SC, ti SC w/SHELL
	SITE #: 026	SITE:	ORLANDO HOTEL NORTHEAST ALTERNATING S & SC, ti SC w/SHELL
	SITE #: 027	SITE:	JACKSONVILLE COAL TERMINAL B-20 FINE SAND, ti FINE SAND

SITE #:	028	SITE:	JACKSONVILLE COAL TERMINAL B-21 FINE SAND/SILTY SAND, ti FINE SAND
SITE #:	029	SITE:	ALACHUA COUNTY LANDFILL ***NO PLT** SAND
SITE #:	030	SITE:	WEST BAY ***NO PLT*** SAND, SILTY SAND, CLAYEY SAND
SITE #:	031	SITE:	LAKE WAUBERG ***NO PLT*** LIMITED DATA--CLAY SAMPLE

SITE #: 001 SITE: APALACHICOLA RIVER BRIDGE-PIER 3

PILE:				
DIA:	24 in	TYPE:	PS C V
AREA:	463 in^2	SHAPE:	SQ
LENGTH:	93.25 ft	TIP IN:	
GSE:	7.62 ft	TIP EL:	-85.5 ft
GWT:	0 ft		

GEN SOIL:50' CLAYEY SAND / 10'STIFF CLAY / CLAYEY SAND

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P001	860917		DRIVING DATE
ECPT	C001A	880620	APR3-1	10t/yellow
	C001B	880620	APR3-2	10t
MCPT	M001A	861014	C-P2	
	M001B	861020	C-P3	
	M001C	861020	C-P5	
	M001D	861020	C-P6	
SPT	S001A	790404	HOLE 1	
	S001B	790404	HOLE 2	
	S001C	790404	HOLE 3	
	S001D	781108	HOLE 4	
	S001E	781108	HOLE 5	
	S001F	781108	HOLE 6	
	S001G	781108	HOLE 7	
	S001H		HOLE 10	SPATIAL VARIABILITY STUDY
	S001I		HOLE 11	SPATIAL VARIABILITY STUDY
	S001J		HOLE 12	SPATIAL VARIABILITY STUDY
	S001K		HOLE 13	SPATIAL VARIABILITY STUDY
	S001L		HOLE 14	SPATIAL VARIABILITY STUDY
	S001M		HOLE 15	SPATIAL VARIABILITY STUDY
	S001N		HOLE 16	SPATIAL VARIABILITY STUDY
	S001O		HOLE 17	SPATIAL VARIABILITY STUDY
	S001P		HOLE 18	SPATIAL VARIABILITY STUDY
	S001Q		HOLE 19	SPATIAL VARIABILITY STUDY
	S001R		HOLE 20	SPATIAL VARIABILITY STUDY
	S001S		HOLE 21	SPATIAL VARIABILITY STUDY
	S001T		HOLE 22	SPATIAL VARIABILITY STUDY
B-LOG	B001A	790404	HOLE 1	
	B001B	790404	HOLE 2	
	B001C	790404	HOLE 3	

B001D	781108	HOLE 4
B001E	781108	HOLE 5
B001F	781108	HOLE 6
B001G	781108	HOLE 7

SITE #: 002 SITE: APALACHICOLA RIVER BRIDGE-FLAT SLAB BENT 16

PILE:				
	DIA:	18 in	TYPE:	PS C S
	AREA:	324 in^2	SHAPE:	SQ
	LENGTH:	65.23 ft	TIP IN:	
	GSE:	9.18 ft	TIP EL:	-55.61
	GWT:	0 ft		

GEN SOIL:50' SANDY CLAY/CLAY OVER 10' SAND OVER CLAYEY SAND

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P002	861013		DATE DRIVEN
ECPT	C002A	880621	APRB16	10t
	C002B	880621	ARB16B	10t
MCPT	M002A	841206	SND #3	
	M002B	841206	SND #2	

SITE #: 003 SITE: APALACHICOLA BAY BRIDGE-FLAT SLAB BENT 22

PILE:				
	DIA:	18 in	TYPE:	PS C S
	AREA:	324 in^2	SHAPE:	SQ
	LENGTH:	72 ft	TIP IN:	
	GSE:	6 ft	TIP EL:	-60.29
	GWT:	ft		

GEN SOIL:MAYBE 40' CLAY OVER SANDY CLAY W/ SHELL

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P003	860917		Sta 316+07 8.5' RT CL
ECPT	C003A	880621	ABB33C	10t
	C003B	880621	ABB33D	10t
MCPT	M003A	841212	SND #7	Sta 314+00 10' RT CL
	M003B	841213	SND #8	Sta 315+00 10' RT CL
	M003C	841213	SND #9	Sta 316+00 10' RT CL
	M003D	841213	SND #10	Sta 317+00 10' RT CL

SITE #: 004 SITE: OVERSTREET BRIDGE-PIER 11

PILE:	DIA:	24 in	TYPE:	PS C	
	AREA:	576 in^2	SHAPE:	SQ	
	LENGTH:	85 ft	TIP IN:		
	GSE:	5.5 ft	TIP EL:		-58.8 ft
	GWT:	ft			

GEN SOIL:10' S & CS/20' CLAY/15' SAND/10' STIFF C/SHELLY SAND

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P004	870402		STA 303+09
ECPT	C004A	880622	OVP11-1	10t
	C004B	880622	OVP11-2	15t/red
	C004C	880622	OVP11-3	15t/red
	C004D	880622	OVP11-4	15t/red
SPT	S004A	790219	HOLE #1	
	S004B	790219	HOLE #2	
B-LOG	B004A	790219	HOLE #1	
	B004B	790219	HOLE #2	

SITE #: 005 SITE: OVERSTREET BRIDGE-PIER 16

PILE:	DIA:	24 in	TYPE:	PS C	
	AREA:	576 in^2	SHAPE:	SQ	
	LENGTH:	72 ft	TIP IN:		
	GSE:	5.2 ft	TIP EL:		-60.4 ft
	GWT:	ft			

GEN SOIL:25' C & SC/10' CS/10' S/20' SC & C/CS WITH SHELL

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P005	870416		STA 312+49
ECPT	C005A	880622	OVP16D	(#1)/15t/yellow
	C005B	880622	OVP16G	(#2)/10t
	C005C	880623	OVP16H	(#3)/10t
	C005D	880623	OVP16I	(#4)/15t/yellow
SPT	S005A	790219	HOLE #5	
	S005B	790219	HOLE #6	
	S005C	790302	HOLE #7	
	S005D	790302	HOLE #E-7	
B-LOG	B005A	790219	HOLE #5	
	B005B	790219	HOLE #6	
	B005C	790302	HOLE #7	
	B005D	790302	HOLE #E-7	

SITE #: 006 SITE: SARASOTA HOSP GARAGE-SP7

PILE:				
DIA:	12 in	TYPE:	PC CONC
AREA:	144 in^2	SHAPE:	SQ
LENGTH:	35 ft	TIP IN:	ROCK
GSE:	3 ft	TIP EL:	-22.08 ft
GWT:	0 ft		

GEN SOIL:23' FINE SAND ON 5'LAYER OF ROCK (LIMEROCK)

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P006	880720	TP6	LOCATION APPROX
	P007	880727	TP8	REDRIVEN-LOCATION APPROX
ECPT	C006A	880718	SHSP7A	BEFORE PILE/10t
	C006B	880718	SHSP7B	BEFORE PILE/15t
	C006C	880719	SHSP7C	AFTER PILE/15t
	C006D	880719	SHSP7D	AFTER PILE/15t
SPT	S006A	880228	SP-7	
	S006B	880228	SP-6	
	S006C	880228	SP-1	
	S006D	880228	SP-10	
B-LOG	B006A	880228	SP-7	
	B006B	880228	SP-6	
	B006C	880228	SP-1	
	B006D	880228	SP-10	

SITE #: 007 SITE: SARASOTA HOSP GARAGE-SP5

PILE:			
DIA:	12 in	TYPE:	PC CONC
AREA:	144 in^2	SHAPE:	SQ
LENGTH:	35 ft	TIP IN:	ROCK
GSE:	3 ft	TIP EL:	-22 ft
GWT:	0 ft		

GEN SOIL:28' FINE SAND OVER 4' SILT OVER ROCK

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P007	880727	TP8	REDRIVEN-LOCATION APPROX
	P006	880720	TP6	LOCATION APPROX
ECPT	C007A	880718	SHSP5A	BEFORE PILE/15t
	C007B	880718	SHSP5B	BEFORE PILE/15t
	C007C	880719	SHSP5C	AFTER PILE/15t/red
	C007D	880719	SHSP5E	AFTER PILE/15t
SPT	S007A	880228	SP-5	
	S007B	880228	SP-2	
	S007C	880228	SP-3	
	S007D	880228	SP-8	
	S007E	880228	SP-9	
B-LOG	B007A	880228	SP-5	

B007B	880228	SP-2
B007C	880228	SP-3
B007D	880228	SP-8
B007E	880228	SP-9

SITE #: 008 SITE: SARASOTA CONDO

PILE:	DIA:	14 in	TYPE:	PC CONC
	AREA:	196 in^2	SHAPE:	SQ
	LENGTH:	20.5 ft	TIP IN:	ROCK
	GSE:	6 ft	TIP EL:	-9.92 ft
	GWT:	3 ft		

GEN SOIL:3' F. SAND OVER 5' SC OVER 8' F. SAND OVER ROCK SEAM

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P008	880620	TP-3	
	P008T	880628	TP-2	TENSION TEST
ECPT	C008A	880719	SCN01	15t
	C008B	880719	SCN02	15t
SPT	S008A	850315	SPT9	
	S008B	850315	SPT8	
	S008C	850315	SPT7	
	S008D	850315	SPT6	
	S008E	850315	SPT2	
B-LOG	B008A	850315	SPT9	
	B008B	850315	SPT8	
	B008C	850315	SPT7	
	B008D	850315	SPT6	
	B008E	850315	SPT2	

SITE #: 009 SITE: SARASOTA - MANATEE LANDFILL

GEN SOIL:13' FINE SAND OVER 5-18' SC/SILT OVER CS
GWT: 5.5 FT DEPTH

TEST	FILE	DATE	TEST ID	COMMENTS
PLT				NO PLT
ECPT	C009A	880719	MLF48	15t
	C009B	880719	MLF52	15t/yellow
	C009C	880719	MLF54	15t/yellow
SPT	S009A	880707	STA 48+00	
	S009B	880608	STA 52+00	
	S009C	880707	STA 54+00	
B-LOG	B009A	880707	STA 48+00	
	B009B	880608	STA 52+00	
	B009C	880707	STA 54+00	

SITE #: 010 SITE: FT MYERS INTERCHANGE - CONCRETE PILE

PILE:	DIA:	14 in	TYPE:	PS C	
	AREA:	196 in^2	SHAPE:	SQ	
	LENGTH:	70 ft	TIP IN:	SILTY CLAY	
	GSE:	7 ft	TIP EL:		-60 ft
	GWT:	2.5 ft			

GEN SOIL:32' S/70' SANDY & SILTY CLAY/5' CEM SC OVER SAND

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P010	880803	TP-1	
	P010T	880809	TP-1	TENSION TEST
ECPT	C010A	880808	FMC1	15t/red/pp
	C010B	880809	FMC2	5t/pp
	C010C	880809	FMC3	5t/red/pp
	C010D	880915	FMPKWY	5t/pp
	C010E	880915	FM2CM1	5t/red/pp
	C010F	880915	FM2CM3	15t/pp
	C010G	880916	FM1CM1	15t/1cm per s/pp
	C010H	880915	FMP5CM	15t/.5cm per s/pp
SPT	S010A	880727	LAW B4	STA 118+80 70' N
	S010B	-	GREI BR6	STA 120+35
B-LOG	B010A	880727	LAW B4	STA 118+80 70' N
	B010B	-	GREI BR6	STA 120+35

SITE #: 011 SITE: FT MYERS INTERCHANGE - STEEL PILE

PILE:	DIA:	12 in	TYPE:	STEEL PIPE	
	AREA:	113 in^2	SHAPE:	RD	
	LENGTH:	120 ft	TIP IN:	DENSE SAND	
	GSE:	7 ft	TIP EL:		-100 ft
	GWT:	0 ft			

GEN SOIL:32' S/70' SANDY & SILTY CLAY/5' CEM SC OVER SAND

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P011	880813	TP-2	
ECPT	C010A	880808	FMC1	see P010/red
	C010B	880809	FMC2	see P010
	C010C	880809	FMC3	see P010/red
	C010D	880915	FMPKWY	5t/see P010
	C010E	880915	FM2CM1	5t/red/see P010
	C010F	880915	FM2CM3	15t/see P010
	C010G	880916	FM1CM1	15t/1cm per s/see P010
	C010H	880915	FMP5CM	15t/.5cm per s/see P010
SPT	S010A	880727	LAW B4	STA 118+80 70' N
	S010B	-	GREI BR6	STA 120+35
B-LOG	B010A	880727	LAW B4	STA 118+80 70' N
	B010B	-	GREI BR6	STA 120+35

SITE #: 012 SITE: FT MYERS - AIRPORT

GEN SOIL: SAND, SILTY CLAY/CLAYEY SILT, LIMEROCK
GWT: 5 FT DEPTH

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	N/A			
ECPT	C012A	880810	FMAPB2A	15t/pp
	C012B	880916	FMAPB3	15t/yellow/pp
SPT	S012A		B-2	
	S012B		B-3	
B-LOG	B012A		B-2	
	B012B		B-3	

SITE #: 013 SITE: PORT ORANGE BENT 19

PILE:				
DIA:	18 in	TYPE:	
AREA:	324 in^2	SHAPE:	SQ
LENGTH:	34.25 ft	TIP IN:	SHELLY SAND
GSE:	4.2 ft	TIP EL:	-26.68 ft
GWT:	ft		

GEN SOIL: SHELLY SAND, ti SHELLY SAND

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P013	880212		Sta 226+01 44' RT/1ST CYCL
ECPT	C013A	871021		FDOT 226+01 26' LT (Note:0.25 m INCREMENTS)
	C013B	871130		UF DATA
MCPT	M013A	850805	SND #7	Sta 225+41 18' RT
	M013B	850807	SND #6	Sta 225+01 18' RT

SITE #: 014 SITE: PORT ORANGE BENT 2

PILE:				
DIA:	18 in	TYPE:	
AREA:	324 in^2	SHAPE:	SQ
LENGTH:	32.78 ft	TIP IN:	SHELLY SAND
GSE:	6.4 ft	TIP EL:	-23.61 ft
GWT:	ft		

GEN SOIL: SHELLY SAND, ti SHELLY SAND

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P014	880212		Sta 221+25 11' RT
ECPT	C014A	871022		FDOT 221+53 27' LT (Note:0.25 m INCREMENTS)
MCPT	M014A	850805	SND #1	Sta 220+85 70' LT
	M014B	850709	SND #2	Sta 222+00 18' RT
SPT	S014A	850730	BORING #1	Sta 221+90 20' LT
B-LOG	B014A	850730	BORING #1	Sta 221+90 20' LT

SITE #: 015 SITE: WEST PALM I-95 PIER B-4

PILE:	DIA:	18 in	TYPE:	PC CONC
	AREA:	324 in^2	SHAPE:	SQ
	LENGTH:	45.3 ft	TIP IN:	SAND (tr SHELL)
	GSE:	18 ft	TIP EL:	-34.6 ft
	GWT:	6 ft		

GEN SOIL:SAND, ti SAND W/ TRACE SHELL

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P015	850718		
ECPT	C015A	880913	WPB4A	10t
	C015B	880913	WPB4B	10t
	C015C	880914	WPB4C	15t/pp
SPT	S015A	810812	BORING #1	
B-LOG	B015A	810812	BORING #1	

SITE #: 016 SITE: WEST PALM I-95 PIER B-6

PILE:	DIA:	18 in	TYPE:	PC CONC
	AREA:	324 in^2	SHAPE:	SQ
	LENGTH:	57.8 ft	TIP IN:	SAND w/ tr SHELL
	GSE:	33.5 ft	TIP EL:	-30 ft
	GWT:	8 ft		

GEN SOIL:SAND w/ tr SHELL, ti SAND w/ tr SHELL

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	**P016**	850802		PLT NO GOOD-NOT ENTERED
ECPT	C016A	880913	WPB6A	15t/pp
	C016B	880913	WPB6B2	15t/pp
	C016C	880913	WPB6C1	10t
SPT	S016A	810812	BORING #3	
B-LOG	B016A	810812	BORING #3	

SITE #: 017 SITE: WEST PALM I-95 PIER B-9

PILE:	DIA:	18 in	TYPE:	PC CONC
	AREA:	324 in^2	SHAPE:	SQ
	LENGTH:	39.5 ft	TIP IN:	SAND w/ tr SHELL
	GSE:	25 ft	TIP EL:	-30.8 ft
	GWT:	2 ft		

GEN SOIL:SAND w/ tr SHELL, ti SAND w/ tr SHELL

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P017	850727		
ECPT	C017A	880914	WPB9A	15t/pp

	C017B	880914 WPB9B2	10t
SPT	S017A	810812 BORING #5	
B-LOG	B017A	810812 BORING #5	

SITE #: 018 SITE: WEST PALM I-95 PIER C-2

PILE:	DIA:	18 in	TYPE:	PC CONC
	AREA:	324 in^2	SHAPE:	SQ
	LENGTH:	44 ft	TIP IN:	SHELLY SAND
	GSE:	10 ft	TIP EL:	-32.8 ft
	GWT:	4.8 ft		

GEN SOIL:SAND & SHELLY SAND, ti SHELLY SAND

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P018	850809		STA 1982+49 39' RT CL
MCPT	M018A	800611	SND #1	
	M018B	800610	SND #4	
SPT	S018A	800527	BOR #1	
B-LOG	B018A	800527	BOR #1	

SITE #: 019 SITE: CHOCTAWHATCHEE BAY PIER 1

PILE:	DIA:	24 in	TYPE:	PC CONC
	AREA:	576 in^2	SHAPE:	SQ
	LENGTH:	57 ft	TIP IN:	SAND
	GSE:	6 ft	TIP EL:	ft
	GWT:	0 ft		

GEN SOIL:SAND & SILTY SAND, ti SAND

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P019		STA 115+08 60.5' LT CL EXIST	
ECPT	C019A	880927	CBP1A	10t/pp/STA 115+02 50' LT
	C019B	880927	CBP1B	10t/pp/STA 114+00 25' LT
	C019C	890110	CBP1C	10t/pp (AFTER)/STA 115+28
	C019D	890110	CB111	10t/pp/STA 111+00 25' LT
	C019E	890110	CB1450	STA 114+50 37' LT/10t
	C019F	890111	CB1600	STA 116+00 42.5' LT/10t
	C019G	890111	CB1700	STA 117+00 43' LT/10t
	C019H	890111	CB1800	STA 118+00 40.5' LT/10t
	C019I	890111	CB1900	STA 119+00 43' LT/10t
	C019J	890301	FDOT	STA 111+06 33' LT/10t
	C019K	890302	FDOT	STA 110+88 31' LT/10t
	C019L	880928		STA 119+46.5 38' LT/10t
	C019M	880928		STA 114+78 31' LT/10t
MCPT	M019A	850205	SND #15	STA 115+02 22' LT
SPT	S019A	850200	BOR #2	STA 114+00 21'LT
	S019B	850200	BOR #1	STA 111+00 20' LT
	S019C	850200	BOR #3	STA 117+00 28' LT

B-LOG	B019A	850200	BOR #2	STA 114+00 21'LT
	B019B	850200	BOR #1	STA 111+00 20' LT
	B019C	850200	BOR #3	STA 117+00 28' LT

SITE #: 020 SITE: CHOCTAWHATCHEE BAY PIER 4

PILE:	DIA:	30 in	TYPE:	PC CONC
	AREA:	900 in^2	SHAPE:	SQ
	LENGTH:	90 ft	TIP IN:	SAND
	GSE:	6 ft	TIP EL:	ft
	GWT:	0 ft		

GEN SOIL:SAND, SOME CLAY, ti SAND

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P020			STA 119+28 50' LT CL EXIST
ECPT	C020A	880927	CBP4A	10t/pp/STA 119+28 50' LT
	C020B	880927	CBP4B	10t/pp/STA 120+00 38' LT
MCPT	M020A	850206	SND #17	STA 119+00 22' LT
	M020B	850604	SND #47	STA 120+00 22' LT
SPT	S020A	850300	BOR #4	STA 120+00 33' LT
B-LOG	B020A	850300	BOR #4	STA 120+00 33' LT

SITE #: 021 SITE: CHOCTAWHATCHEE BAY FSB 26

PILE:	DIA:	24 in	TYPE:	PC CONC
	AREA:	576 in^2	SHAPE:	SQ
	LENGTH:	84 ft	TIP IN:	SAND
	GSE:	6 ft	TIP EL:	ft
	GWT:	0 ft		

GEN SOIL:probably SAND, SOME CLAY, ti SAND

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P021			STA 183+16 50' LT CL EXIST
ECPT	C021A	880928	CBF26B	10t/pp/Sta 183+16 26'LT
	C021B	880928	CBF26D	10t/pp/Sta 182+61 26.5'LT
	C021C	890110	CBF26F	pp/10t/STA 182+99 26' LT AFTER PILE DRIVING
	C021D	890111	CB8058	pp/10t/STA 180+58 27' LT
MCPT	M021A		SND #2	Sta 183+00 30' LT
	M021B	850213	SND #21	Sta 182+00 22' LT
	M021C	850213	SND #22	STA 184+00 22' LT
SPT	S021A	850200	BOR #27	STA 180+50 40' LT
B-LOG	B021A	850200	BOR #27	STA 180+50 40' LT

SITE #: 022 SITE: WHITE CITY

PILE:	DIA:	in	TYPE:	
	AREA:	in^2	SHAPE:	
	LENGTH:	ft	TIP IN:	
	GSE:	ft	TIP EL:	ft
	GWT:	DEPTH 8 ft		

GEN SOIL:probably SAND, SOME CLAY

TEST	FILE	DATE	TEST ID	COMMENTS
ECPT	C022A	880929	WCB2A	STA 7+95 30.5' RT CL EXIST
	C022B	880929	WCB10A	STA 22+25 67' RT CL EXIST/
	C022C	880929	WCB11A	STA 23+85 65'RT CL EXIST/1
MCPT	M022A	851219	SND #16	STA 8+00 65' RT CL EXIST
	M022B	851211	SND #2	STA 22+18 65' RT CL EXIST
	M022C	851211	SND #4	STA 24+00 65' RT CL EXIST
SPT	S022A	851114	BOR #2	STA 8+00 55' RT CL EXIST
	S022B	851114	BOR #10	STA 22+30 65' RT CL EXIST
	S022C	851220	BOR #11	STA 23+91 73' RT CL EXIST
B-LOG	B022A	851114	BOR #2	STA 8+00 55' RT CL EXIST
	B022B	851114	BOR #10	STA 22+30 65' RT CL EXIST
	B022C	851220	BOR #11	STA 23+91 73' RT CL EXIST

SITE #: 023 SITE: ORLANDO ARENA *****DEPTH IN FEET*****

PILE:	DIA:	14 in	TYPE:	PC CONC
	AREA:	196 in^2	SHAPE:	SQ
	LENGTH:	94 ft	TIP IN:	CLAYEY SAND
	GSE:	98 ft	TIP EL:	4 ft
	GWT:	83 ft		

GEN SOIL:43' SAND OVER CLAYEY SAND

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P023	870118	TP6	PREDRILLED TO 48'
	P023T	870121	TP6	TENSION TEST
ECPT	C023A	861208	CS-3A	pp/***DEPTH IN FT***
	C023B	861208	CS-4	***DEPTH IN FT***
	C023C	861208	CS-8	***DEPTH IN FT***
	C023D	861208	CS-9	***DEPTH IN FT***
SPT	S023A	861100	TB-2	
	S023B	861100	TB-3	
	S023C	861100	TB-12	
	S023D	861100	TB-14	
	S023E	861100	TB-15	
B-LOG	B023A	861100	TB-2	
	B023B	861100	TB-3	
	B023C	861100	TB-12	
	B023D	861100	TB-14	
	B023E	861100	TB-15	

SITE #: 024 SITE: ORLANDO HOTEL SOUTH *****DEPTH IN FT*****

PILE:	DIA:	14 in	TYPE:	PC CONC
	AREA:	196 in^2	SHAPE:	SQ
	LENGTH:	120 ft	TIP IN:	CLAYEY SAND w/SHE
	GSE:	say 0 ft	TIP EL:	-96.25 ft
	GWT:	-11.5 ft		

GEN SOIL:ALTERNATING SAND AND CLAYEY SAND LAYERS

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P024	870924	TP-I	PREDRILLED 20'/TOP 5' OVERBURDEN REMOVED
ECPT	C024A	870916	CP-1	pp
	C024B	870927	CP-7	pp
SPT	S024A	870200	TB-2	
	S024B	870200	TB-1	
B-LOG	B024A	870200	TB-2	
	B024B	870200	TB-1	

SITE #: 025 SITE: ORLANDO HOTEL NORTH *****DEPTH IN FEET****

PILE:	DIA:	14 in	TYPE:	PC CONC
	AREA:	196 in^2	SHAPE:	SQ
	LENGTH:	120 ft	TIP IN:	CLAYEY SAND w/SHE
	GSE:	say 0 ft	TIP EL:	-94.75 ft
	GWT:	-11.5 ft		

GEN SOIL:ALTERNATING SAND AND CLAYEY SAND LAYERS

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P025	870930	TP-H	PREDRILLED 20'/TOP 5' OVERBURDEN REMOVED
ECPT	C025A	870917	CP-2	pp
SPT	S026A	870200	TB-3	
B-LOG	B026A	870200	TB-3	

SITE #: 026 SITE: ORLANDO HOTEL NORTHEAST ****DEPTH IN FEET

PILE:	DIA:	14 in	TYPE:	PC CONC
	AREA:	196 in^2	SHAPE:	SQ
	LENGTH:	75 ft	TIP IN:	CLAYEY SAND w/SHE
	GSE:	say 0 ft	TIP EL:	-74 ft
	GWT:	-11.5 ft		

GEN SOIL:ALTERNATING SAND AND CLAYEY SAND LAYERS

TEST	FILE	DATE	DIST(ft)	DIR	COMMENTS
PLT	P026	871002	0	0	TP-A/PREDRILLED 1

ECPT	C026A	870920	7	190 CP-5A/pp
SPT	S026A	870200	20.5	210 TB-3
B-LOG	B026A	870200	20.5	210 TB-3

SITE #: 027 SITE: JACKSONVILLE COAL TERMINAL B-20

PILE:	DIA:	20 in	TYPE:	PC CONC
	AREA:	400 in^2	SHAPE:	SQ
	LENGTH:	55 ft	TIP IN:	FINE SAND
	GSE:	6 ft	TIP EL:	-40.2 ft
	GWT:	0 ft		

GEN SOIL:FINE SAND

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P027	870503		LOCATION APPROXIMATE
	P027T	870506		TENSION TEST
ECPT	C027A	881107	JXB20A	10t/pp/yellow
	C027B	881107	JXB20B	10t/pp/yellow
	C027C	881107	JXB20C	15t/pp
SPT	S027A	791002		LOCATION APPROXIMATE
B-LOG	B027A	791002		LOCATION APPROXIMATE

SITE #: 028 SITE: JACKSONVILLE COAL TERMINAL B-21

PILE:	DIA:	20 in	TYPE:	PC CONC
	AREA:	400 in^2	SHAPE:	SQ
	LENGTH:	40 ft	TIP IN:	FINE SAND
	GSE:	13 ft	TIP EL:	-23.4 ft
	GWT:	3 ft		

GEN SOIL:FINE SAND & SILTY SAND

TEST	FILE	DATE	TEST ID	COMMENTS
PLT	P028	870429		LOCATION ESTIMATED
	P028T	870501		TENSION TEST
ECPT	C028A	881107	JXB21A	15t/pp/yellow
	C028B	881107	JXB21B	10t/pp
SPT	S028A	791220		LOCATION ESTIMATED
B-LOG	B028A	791220		LOCATION ESTIMATED

SITE #: 029 SITE: ALACHUA COUNTY LANDFILL ***NO PLT***

GEN SOIL:SAND

TEST	FILE	DATE	TEST ID	COMMENTS
ECPT	C029A	880600	DMTSPT3	10t
	C029B	880600	DMTCPT3	10t

	C029C	880600	DMT4	10t
	C029D	880600	DMT5	10t
	C029E	880600	DMT6	10t
	C029F	880600	DMT7	10t
	C029G	880600	DMT9	10t
SPT	S029A	870616	R3	
	S029B	870615	R1	
B-LOG	B029A	870616	R3	
	B029B	870615	R1	

SITE #: 030 SITE: WEST BAY ***NO PLT***

GEN SOIL:SAND, SILTY SAND, CLAYEY SAND

TEST	FILE	DATE	TEST ID	COMMENTS
ECPT	C030A	880500		STA 284+00 18' LT
	C030B	880500		STA 285+50 18' LT
	C030C	880500		STA 288+95 23' LT
	C030D	880500		STA 303+96.5 52' LT
	C030E	880500		STA 306+12 42' LT
	C030F	880500		STA 309+71.5 CL
SPT	S030A	851200		STA 284+00 27' LT
	S030B	851200		STA 285+50 20' LT
	S030C	851200		STA 289+00 46' LT
	S030D	851200		STA 304+00 43' LT
	S030E	851200		STA 306+00 19' LT
	S030F	851200		STA 309+75 18' LT

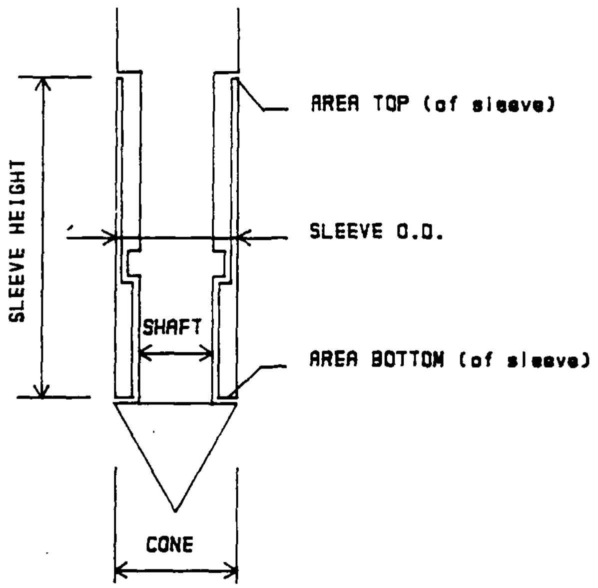
SITE #: 031 SITE: LAKE WAUBERG ***NO PLT***

GEN SOIL:SAND, CLAY

TEST	FILE	DATE	TEST ID	COMMENTS
ECPT	C031A		DMT20	CORRELATE WITH LAB SAMPLE

APPENDIX B

PENETROMETER TIP MEASUREMENTS AND UNEQUAL END AREA CALCULATIONS



Definition of Penetrometer Tip Measurements

Example (10-ton penetrometer tip)

$$q_c \text{ Correction} = P\,(A_{cone} - A_{shaft}) \,/\, (A_{cone})$$

$$= P\,(9.909\text{ cm}^2 - 6.492\text{ cm}^2) \,/\, 9.909\text{ cm}^2$$

$$= 0.345\,P\,(0.1\text{ MPa/bar}) = \underline{0.034\text{ MPa/bar}}$$

$$f_s \text{ Correction} = P\,(A_{bottom} - A_{top}) \,/\, (A_{sleeve})$$

$$= P\,(3.355\text{ cm}^2 - 1.863\text{ cm}^2) \,/\, 148.5\text{ cm}^2$$

$$= 0.01005\,P\,(100\text{ kPa/bar}) = \underline{1.005\text{ kPa/bar}}$$

Data

	5-TON	10-TON	15-TON
Cone diameter	3.552 cm	3.552 cm	4.351 cm
Cone Area	9.909 cm2	9.909 cm2	14.869 cm2
Shaft Diameter	2.490 cm	2.875 cm	3.590 cm
Shaft Area	4.870 cm2	6.492 cm2	10.122 cm2
Area bottom	5.000 cm2	3.355 cm2	4.676 cm2
Area top	1.859 cm2	1.863 cm2	3.507 cm2
Sleeve Height	13.283 cm	13.282 cm	10.885 cm
Sleeve OD	3.558 cm	3.559 cm	4.348 cm
Sleeve Area	148.475 cm2	148.505 cm2	148.685 cm2
Pressure Effect			
q_c (per bar)	0.051 MPa	0.034 MPa	0.032 MPa
f_s (per bar)	2.116 kPa	1.005 kPa	0.786 kPa

APPENDIX C

SUMMARY OF LABORATORY CLASSIFICATION OF SOILS

SITE	DEPTH (m)	q_c (MPa)	f_s (KPa)	USCS[1]	SOIL TYPE[2]	CATEGORY[3]
C019B	2.00	3.00	0	S	9	S
C019B	6.00	0.33	0	T	14	C
C019B	9.00	0.37	0	T	7	M
C019B	13.00	0.68	0	S	19	S
C019B	16.00	7.76	13	S	19	S
C019B	21.00	1.42	13	C	3	C
C019B	23.00	1.35	16	C	3	C
C019B	35.50	2.56	30	T	16	U
C019D	1.50	7.74	2	S	9	S
C019D	3.00	3.47	3	S	9	S
C019D	8.00	2.10	0	S	7	M
C019D	17.00	1.16	12	C	3	C
C019D	22.50	9.93	6	T	29	S
C019D	28.70	10.46	24	T	14	C
C021D	3.00	3.52	17	S	9	S
C021D	9.80	5.70	27	S	9	S
C021D	18.30	18.70	101	S	9	S
C021D	24.25	24.93	143	T	16	U
C022A	9.5	2.45	0	T	9	S
C022A	11.0	0.59	0	C	3	C

C022A	15.5	35.75	134	T	9	S
C022A	17.2	36.12	81	T	9	S
C022A	21.0	8.06	39	T	9	S
C022A	27.0	9.35	54	S	9	S
C022A	30.0	13.16	62	S	9	S
C022A	34.5	12.68	47	T	17	U
C022A	35.5	7.40	102	T	17	U
C022B	2.30	2.65	171	T	3	C
C022B	11.50	24.92	179	T	9	S
C022B	15.50	30.10	85	S	9	S
C022B	17.50	4.90	31	T	9	S
C022B	19.50	7.19	28	T	9	S
C022C	4.80	4.55	0	C	9	S
C022C	9.00	28.02	83	T	9	S
C022C	12.00	31.51	114	T	9	S
C022C	15.50	1.24	26	T	14	C
C022C	20.00	12.77	61	T	9	S
C022C	26.00	6.65	17	T	9	S
C030E	2.00	5.48	32	S	9	S
C030E	11.00	23.66	150	S	9	S
C030E	16.00	19.64	62	S	16	U
C030E	27.00	0.43	9	T	16	U
C030E	32.00	4.28	35	T	16	U
C030B	7.50	6.94	20	S	9	S
C030B	10.50	6.47	20	S	9	S
C030C	7.50	1.80	3	T	16	U
C030C	25.00	5.55	3	T	17	U

C030C	33.00	4.85	16	T	16	U
C030A	1.00	9.01	68	T	9	S
C030A	6.00	2.00	11	T	9	S
C030A	8.00	2.30	6	T	9	S
C030A	11.00	2.32	2	T	9	S
C030A	13.00	0.49	3	T	14	C
C030D	10.00	8.74	60	T	16	U
C030D	25.00	6.53	8	T	17	U
C030D	30.00	4.75	16	T	16	U
C030D	35.00	5.86	15	T	16	U
C030F	7.00	6.66	40	T	9	S
C030F	11.00	9.07	40	T	9	S
C030F	23.00	3.83	24	M	17	U
C030F	30.00	3.73	13	M	17	U
C030F	34.00	5.37	13	M	17	U
C024A	18.59	1.57	19.6	U	16	U
C024B	18.29	1.18	0	U	16	U
C026A	15.54	0.59	29.4	U	16	U
C006A	6.10	12.37	49	T	8	T
C006B	6.10	9.56	57	T	8	T
C007A	0.61	3.55	7	T	8	T
C007A	2.44	8.07	35	T	8	T
C007A	6.10	11.26	67	T	8	T
C008A	4.57	23.01	134	T	16	U
C008B	1.52	5.15	107	T	14	C
C008B	4.57	7.22	103	T	16	U
C012B	20.27	2.35	69	M	5	M

C012B	14.17	1.31	21	U	4	C
C031A	2.05	3.94	222	C	14	C
C031A	2.25	4.33	260	M	3	C
C031A	2.50	3.52	202	M	3	C

Notes:

1. Classification based on the Unified Soil Classification System. Applicable references include ASTM Standard D 2487 (2) and U.S. Army Corps of Engineers Manual EM 1110-2-1906 (61).

2. Soil types based on placement of soil description from SPT logs into one of 30 categories (Soil types #1 through #12 taken from Robertson et al. (44) classification chart):

1. Sensitive fine grained
2. Organic material
3. Clay
4. Silty clay to clay
5. Clayey silt to silty clay
6. Sandy silt to clayey silt
7. Silty sand to sandy silt
8. Sand to silty sand
9. Sand
10. Gravelly sand to sand
11. Very stiff fine grained--overconsolidated or cemented
12. Sand to clayey sand--overconsolidated or cemented
13. Shelly sand
14. Sandy clay
15. Sandy clay with shell
16. Clayey sand
17. Clayey sand with shell
18. Clayey sand with rock
19. Sand with organics
20. Clay with organics
21. Clay with shell
22. Rock or limestone
23. Fragmented or weathered rock
24. Fine sand with rock
25. Sandy silt with rock
26. Sandy silt with shell
27. Silty sand with shell
28. Sandy silty clay
29. Cemented sand
30. Cemented clayey sand

3. Categories group similar soil types:

O Organic material (Soil type 2)
C Clay (Soil types 1, 3, 4, 11, 14, 15, 20, 21, 28)
M Silt (Soil types 5, 6, 7, 25, 26)
U Clayey sand (Soil types 16, 17, 18, 30)
T Silty sand (Soil types 8, 27)
S Sand (Soil types 9, 10, 12, 13, 19, 24, 29)
R Rock (Soil types 22, 23)

APPENDIX D
DISCRIMINANT ANALYSIS CLASSIFICATION SUMMARIES

PROCEDURE DISCRIM   CLASSIFIED BY: USCS CATEGORY   DATA: LAB

COUNT

TO / FROM	C	M	S	T	U	TOTALS
C	0	1	0	0	3	4
M	1	2	1	2	0	6
S	0	0	10	4	0	14
T	2	5	17	15	3	42
U	1	0	0	0	2	3
TOTALS	4	8	28	21	8	69

PERCENTAGE

TO / FROM	C	M	S	T	U	TOTALS
C	0.0	25.0	0.0	0.0	75.0	100.0
M	16.7	33.3	16.7	33.3	0.0	100.0
S	0.0	0.0	71.4	28.6	0.0	100.0
T	4.8	11.9	40.5	35.7	7.1	100.0
U	33.3	0.0	0.0	0.0	66.7	100.0

PROCEDURE DISCRIM   CLASSIFIED BY: USCS CATEGORY   DATA: NORMAL LAB

COUNT

TO / FROM	C	M	S	T	U	TOTALS
C	0	1	0	0	3	4
M	1	3	0	2	0	6
S	0	0	10	4	0	14
T	2	4	20	13	3	42
U	1	0	0	0	2	3
TOTALS	4	8	30	19	8	69

PERCENTAGE

TO / FROM	C	M	S	T	U	TOTALS
C	0.0	25.0	0.0	0.0	75.0	100.0
M	16.7	50.0	0.0	33.3	0.0	100.0
S	0.0	0.0	71.4	28.6	0.0	100.0
T	4.8	9.5	47.6	31.0	7.1	100.0
U	33.3	0.0	0.0	0.0	66.7	100.0

PROCEDURE NEIGHBOR   CLASSIFIED BY: USCS CATEGORY   DATA: LAB

COUNT

TO / FROM	C	M	S	T	U	TOTALS
C	3	1	0	0	0	4
M	0	6	0	0	0	6
S	0	2	7	5	0	14
T	2	11	8	18	3	42
U	2	0	0	0	1	3
TOTALS	7	20	15	23	4	69

PERCENTAGE

TO / FROM	C	M	S	T	U	TOTALS
C	75.0	25.0	0.0	0.0	0.0	100.0
M	0.0	100.0	0.0	0.0	0.0	100.0
S	0.0	14.3	50.0	35.7	0.0	100.0
T	4.8	26.2	19.0	42.9	7.1	100.0
U	66.7	0.0	0.0	0.0	33.3	100.0

PROCEDURE NEIGHBOR   CLASSIFIED BY: USCS CATEGORY   DATA: NORMAL LAB

COUNT

TO / FROM	C	M	S	T	U	TOTALS
C	3	1	0	0	0	4
M	0	6	0	0	0	6
S	0	0	10	4	0	14
T	3	11	12	15	1	42
U	3	0	0	0	0	3
TOTALS	9	18	22	19	1	69

PERCENTAGE

TO / FROM	C	M	S	T	U	TOTALS
C	75.0	25.0	0.0	0.0	0.0	100.0
M	0.0	100.0	0.0	0.0	0.0	100.0
S	0.0	0.0	71.4	28.6	0.0	100.0
T	7.1	26.2	28.6	35.7	2.4	100.0
U	100.0	0.0	0.0	0.0	0.0	100.0

PROCEDURE DISCRIM CLASSIFIED BY: SOIL TYPE DATA: FIELD

COUNT

TO CATEGORY		O	C	M	T	S	S	C
TO SOIL		2	3	7	8	9	13	14
FROM SOIL	#							
O	2	20	5	0	0	0	0	0
C	3	14	282	45	5	4	0	9
SM-MS	7	0	10	106	1	5	2	9
S-SM	8	0	16	6	464	255	110	110
S	9	6	59	120	341	287	211	318
Ssh	13	0	7	10	17	13	6	6
CS	14	1	82	30	10	10	16	27
CSsh	15	0	1	0	1	0	0	0
SC	16	5	60	41	33	74	14	133
SCsh	17	0	2	0	13	15	5	96
So	19	0	0	2	3	6	4	2
Csh	21	0	0	1	0	0	0	0
WRk	23	0	0	0	8	1	0	0
Scem	29	0	9	16	10	8	2	8
SCcem	30	0	0	9	0	0	1	45
	TOTALS	46	533	386	906	678	371	763

TO CAT	C	U	U	S	C	R	S	U	TOTALS
TO SOIL	15	16	17	19	21	23	29	30	
FROM SOIL									
2	0	0	0	0	1	0	0	0	26
3	8	0	0	0	0	0	1	0	368
7	5	0	2	0	10	0	0	0	150
8	550	16	53	9	1	420	60	28	2098
9	169	121	131	58	53	589	273	188	2924
13	37	1	7	2	10	16	32	4	168
14	34	12	7	15	31	4	6	13	298
15	4	0	0	0	0	4	0	0	10
16	152	112	36	39	6	1	265	76	1047
17	64	84	26	31	0	4	80	61	481
19	1	0	0	0	1	0	6	1	26
21	0	0	0	0	17	0	0	0	18
23	1	0	0	0	0	28	5	0	43
29	10	7	1	6	0	53	133	6	269
30	0	20	0	10	0	0	29	47	161
TOTALS	1035	373	263	170	130	1119	890	424	8087

PROCEDURE DISCRIM   CLASSIFIED BY: SOIL TYPE   DATA: FIELD

PERCENTAGE

TO CATEGORY		O	C	M	T	S	S	C
TO SOIL		2	3	7	8	9	13	14
FROM SOIL	#							
O	2	76.9	19.2	0.0	0.0	0.0	0.0	0.0
C	3	3.8	76.6	12.2	1.4	1.1	0.0	2.4
SM-MS	7	0.0	6.7	70.7	0.7	3.3	1.3	6.0
S-SM	8	0.0	0.8	0.3	22.1	12.2	5.2	5.2
S	9	0.2	2.0	4.1	11.7	9.8	7.2	10.9
Ssh	13	0.0	4.2	6.0	10.1	7.7	3.6	3.6
CS	14	0.3	27.5	10.1	3.4	3.4	5.4	9.1
CSsh	15	0.0	10.0	0.0	10.0	0.0	0.0	0.0
SC	16	0.5	5.7	3.9	3.2	7.1	1.3	12.7
SCsh	17	0.0	0.4	0.0	2.7	3.1	1.0	20.0
So	19	0.0	0.0	7.7	11.5	23.1	15.4	7.7
Csh	21	0.0	0.0	5.6	0.0	0.0	0.0	0.0
WRk	23	0.0	0.0	0.0	18.6	2.3	0.0	0.0
Scem	29	0.0	3.3	5.9	3.7	3.0	0.7	3.0
SCcem	30	0.0	0.0	5.6	0.0	0.0	0.6	28.0

TO CAT	C	U	U	S	C	R	S	U	TOTALS
TO SOIL	15	16	17	19	21	23	29	30	
FROM SOIL									
2	0.0	0.0	0.0	0.0	3.8	0.0	0.0	0.0	100.0
3	2.2	0.0	0.0	0.0	0.0	0.0	0.3	0.0	100.0
7	3.3	0.0	1.3	0.0	6.7	0.0	0.0	0.0	100.0
8	26.2	0.8	2.5	0.4	0.0	20.0	2.9	1.3	100.0
9	5.8	4.1	4.5	2.0	1.8	20.1	9.3	6.4	100.0
13	22.0	0.6	4.2	1.2	6.0	9.5	19.0	2.4	100.0
14	11.4	4.0	2.3	5.0	10.4	1.3	2.0	4.4	100.0
15	40.0	0.0	0.0	0.0	0.0	40.0	0.0	0.0	100.0
16	14.5	10.7	3.4	3.7	0.6	0.1	25.3	7.3	100.0
17	13.3	17.5	5.4	6.4	0.0	0.8	16.6	12.7	100.0
19	3.8	0.0	0.0	0.0	3.8	0.0	23.1	3.8	100.0
21	0.0	0.0	0.0	0.0	94.4	0.0	0.0	0.0	100.0
23	2.3	0.0	0.0	0.0	0.0	65.1	11.6	0.0	100.0
29	3.7	2.6	0.4	2.2	0.0	19.7	49.4	2.2	100.0
30	0.0	12.4	0.0	6.2	0.0	0.0	18.0	29.2	100.0

PROCEDURE DISCRIM   CLASSIFIED BY: SOIL TYPE   DATA: NORMAL FIELD

COUNT

TO CATEGORY		O	C	M	T	S	S	C	C
TO SOIL TYPE		2	3	7	8	9	13	14	15
FROM SOIL	#								
O	2	20	5	0	0	0	0	1	0
C	3	2	325	13	0	1	9	6	7
SM-MS	7	0	11	66	0	0	9	56	0
S-SM	8	0	17	76	309	129	126	2	308
S	9	7	57	173	95	222	344	25	386
Ssh	13	0	10	12	7	7	14	11	12
CS	14	2	96	21	1	6	20	19	19
CSsh	15	0	2	0	0	0	2	0	2
SC	16	6	80	96	26	22	27	78	148
SCsh	17	0	4	78	1	4	32	44	24
So	19	0	0	0	0	0	0	0	0
Csh	21	0	0	0	0	0	0	0	0
WRk	23	0	0	0	0	2	2	0	1
Scem	29	0	15	5	0	7	8	3	7
SCcem	30	0	1	3	0	0	1	52	0
TOTALS		37	623	543	439	400	594	297	914

TO CATEGORY	U	U	S	C	R	S	U	TOTALS
TO SOIL TYPE	16	17	19	21	23	29	30	
FROM SOIL								
2	0	0	0	0	0	0	0	26
3	1	0	1	1	0	1	1	368
7	0	0	0	2	0	0	6	150
8	28	6	789	1	213	67	27	2098
9	173	20	650	24	277	320	151	2924
13	4	1	35	6	17	28	4	168
14	42	5	3	38	3	5	18	298
15	0	0	1	0	3	0	0	10
16	235	24	8	14	6	166	111	1047
17	169	30	0	0	3	22	70	481
19	0	0	18	1	0	6	1	26
21	0	0	0	18	0	0	0	18
23	1	0	3	0	23	11	0	43
29	15	1	12	9	95	85	7	269
30	43	15	0	0	3	19	24	161
TOTALS	711	102	1520	114	643	730	420	8087

PROCEDURE DISCRIM   CLASSIFIED BY: SOIL TYPE   DATA: NORMAL FIELD

PERCENTAGE

TO CATEGORY		O	C	M	T	S	S	C	C
TO SOIL TYPE		2	3	7	8	9	13	14	15
FROM SOIL	#								
O	2	76.9	19.2	0.0	0.0	0.0	0.0	3.8	0.0
C	3	0.5	88.3	3.5	0.0	0.3	2.4	1.6	1.9
SM-MS	7	0.0	7.3	44.0	0.0	0.0	6.0	37.3	0.0
S-SM	8	0.0	0.8	3.6	14.7	6.1	6.0	0.1	14.7
S	9	0.2	1.9	5.9	3.2	7.6	11.8	0.9	13.2
Ssh	13	0.0	6.0	7.1	4.2	4.2	8.3	6.5	7.1
CS	14	0.7	32.2	7.0	0.3	2.0	6.7	6.4	6.4
CSsh	15	0.0	20.0	0.0	0.0	0.0	20.0	0.0	20.0
SC	16	0.6	7.6	9.2	2.5	2.1	2.6	7.4	14.1
SCsh	17	0.0	0.8	16.2	0.2	0.8	6.7	9.1	5.0
So	19	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Csh	21	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
WRk	23	0.0	0.0	0.0	0.0	4.7	4.7	0.0	2.3
Scem	29	0.0	5.6	1.9	0.0	2.6	3.0	1.1	2.6
SCcem	30	0.0	0.6	1.9	0.0	0.0	0.6	32.3	0.0

TO CATEGORY	U	U	S	C	R	S	U	TOTALS
TO SOIL TYPE	16	17	19	21	23	29	30	
FROM SOIL								
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0
3	0.3	0.0	0.3	0.3	0.0	0.3	0.3	100.0
7	0.0	0.0	0.0	1.3	0.0	0.0	4.0	100.0
8	1.3	0.3	37.6	0.0	10.2	3.2	1.3	100.0
9	5.9	0.7	22.2	0.8	9.5	10.9	5.2	100.0
13	2.4	0.6	20.8	3.6	10.1	16.7	2.4	100.0
14	14.1	1.7	1.0	12.8	1.0	1.7	6.0	100.0
15	0.0	0.0	10.0	0.0	30.0	0.0	0.0	100.0
16	22.4	2.3	0.8	1.3	0.6	15.9	10.6	100.0
17	35.1	6.2	0.0	0.0	0.6	4.6	14.6	100.0
19	0.0	0.0	69.2	3.8	0.0	23.1	3.8	100.0
21	0.0	0.0	0.0	100.0	0.0	0.0	0.0	100.0
23	2.3	0.0	7.0	0.0	53.5	25.6	0.0	100.0
29	5.6	0.4	4.5	3.3	35.3	31.6	2.6	100.0
30	26.7	9.3	0.0	0.0	1.9	11.8	14.9	100.0

PROCEDURE NEIGHBOR CLASSIFIED BY: SOIL TYPE DATA: FIELD

COUNT

TO CATEGORY		O	C	M	T	S	S	C	C
TO SOIL TYPE		2	3	7	8	9	13	14	15
FROM SOIL	#								
O	2	25	0	0	0	0	0	0	0
C	3	2	319	8	0	0	4	26	1
SM-MS	7	0	2	137	0	0	0	5	1
S-SM	8	1	22	26	995	302	118	138	13
S	9	6	47	80	221	1228	153	209	11
Ssh	13	2	2	10	0	0	118	4	3
CS	14	5	11	16	1	0	13	195	1
CSsh	15	0	0	0	0	0	0	0	10
SC	16	2	19	24	39	45	66	93	5
SCsh	17	0	1	4	1	0	20	22	1
So	19	0	0	0	0	0	0	0	0
Csh	21	0	0	0	0	0	0	0	0
WRk	23	0	0	0	0	0	0	0	0
Scem	29	0	4	9	0	0	11	3	2
SCcem	30	0	0	2	0	0	0	1	0
	TOTALS	43	427	316	1257	1575	503	696	48

TO CATEGORY	U	U	S	C	R	S	U	TOTALS
TO SOIL TYPE	16	17	19	21	23	29	30	
FROM SOIL								
2	0	0	0	1	0	0	0	26
3	1	0	2	0	0	4	1	368
7	0	0	0	4	0	1	0	150
8	126	152	9	0	57	105	34	2098
9	167	295	49	8	61	192	197	2924
13	0	1	5	3	5	8	7	168
14	8	9	4	8	2	11	14	298
15	0	0	0	0	0	0	0	10
16	444	149	12	0	4	55	90	1047
17	11	334	8	0	2	18	59	481
19	0	0	26	0	0	0	0	26
21	0	0	0	18	0	0	0	18
23	0	0	0	0	43	0	0	43
29	2	5	2	2	12	204	13	269
30	0	2	0	0	1	6	149	161
TOTALS	759	947	117	44	187	604	564	8087

PROCEDURE NEIGHBOR CLASSIFIED BY: SOIL TYPE DATA: FIELD

PERCENTAGE

TO CATEGORY		O	C	M	T	S	S	C	C
TO SOIL TYPE		2	3	7	8	9	13	14	15
FROM SOIL	#								
O	2	96.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
C	3	0.5	86.7	2.2	0.0	0.0	1.1	7.1	0.3
SM-MS	7	0.0	1.3	91.3	0.0	0.0	0.0	3.3	0.7
S-SM	8	0.0	1.0	1.2	47.4	14.4	5.6	6.6	0.6
S	9	0.2	1.6	2.7	7.6	42.0	5.2	7.1	0.4
Ssh	13	1.2	1.2	6.0	0.0	0.0	70.2	2.4	1.8
CS	14	1.7	3.7	5.4	0.3	0.0	4.4	65.4	0.3
CSsh	15	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0
SC	16	0.2	1.8	2.3	3.7	4.3	6.3	8.9	0.5
SCsh	17	0.0	0.2	0.8	0.2	0.0	4.2	4.6	0.2
So	19	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Csh	21	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
WRk	23	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Scem	29	0.0	1.5	3.3	0.0	0.0	4.1	1.1	0.7
SCcem	30	0.0	0.0	1.2	0.0	0.0	0.0	0.6	0.0

TO CATEGORY	U	U	S	C	R	S	U	TOTALS
TO SOIL TYPE	16	17	19	21	23	29	30	
FROM SOIL								
2	0.0	0.0	0.0	3.8	0.0	0.0	0.0	100.0
3	0.3	0.0	0.5	0.0	0.0	1.1	0.3	100.0
7	0.0	0.0	0.0	2.7	0.0	0.7	0.0	100.0
8	6.0	7.2	0.4	0.0	2.7	5.0	1.6	100.0
9	5.7	10.1	1.7	0.3	2.1	6.6	6.7	100.0
13	0.0	0.6	3.0	1.8	3.0	4.8	4.2	100.0
14	2.7	3.0	1.3	2.7	0.7	3.7	4.7	100.0
15	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0
16	42.4	14.2	1.1	0.0	0.4	5.3	8.6	100.0
17	2.3	69.4	1.7	0.0	0.4	3.7	12.3	100.0
19	0.0	0.0	100.0	0.0	0.0	0.0	0.0	100.0
21	0.0	0.0	0.0	100.0	0.0	0.0	0.0	100.0
23	0.0	0.0	0.0	0.0	100.0	0.0	0.0	100.0
29	0.7	1.9	0.7	0.7	4.5	75.8	4.8	100.0
30	0.0	1.2	0.0	0.0	0.6	3.7	92.5	100.0

PROCEDURE NEIGHBOR   CLASSIFIED BY: SOIL TYPE   DATA: NORMAL FIELD

COUNT

TO CATEGORY		O	C	M	T	S	S	C	C
TO SOIL TYPE		2	3	7	8	9	13	14	15
FROM SOIL	#								
O	2	26	0	0	0	0	0	0	0
C	3	3	321	8	0	0	7	18	3
SM-MS	7	1	0	136	0	0	1	3	3
S-SM	8	1	9	38	1182	353	110	65	11
S	9	7	53	69	270	1382	157	169	13
Ssh	13	1	2	11	0	0	122	1	3
CS	14	12	19	19	0	0	9	173	1
CSsh	15	0	0	0	0	0	0	0	10
SC	16	4	29	70	33	45	44	78	4
SCsh	17	0	4	49	0	0	11	26	2
So	19	0	0	0	0	0	0	0	0
Csh	21	0	0	0	0	0	0	0	0
WRk	23	0	0	0	0	0	0	0	1
Scem	29	0	5	4	0	0	15	6	3
SCcem	30	0	0	18	0	0	0	1	0
	TOTALS	55	442	422	1485	1780	476	540	54

FROM SOIL	U	U	S	C	R	S	U	TOTALS
	16	17	19	21	23	29	30	
2	0	0	0	0	0	0	0	26
3	1	1	0	0	1	4	1	368
7	0	0	0	0	0	0	6	150
8	80	84	18	0	36	100	11	2098
9	149	206	31	6	65	233	114	2924
13	0	1	7	5	7	6	2	168
14	3	14	0	16	1	16	15	298
15	0	0	0	0	0	0	0	10
16	437	146	4	8	9	48	88	1047
17	24	284	5	0	4	17	55	481
19	0	0	26	0	0	0	0	26
21	0	0	0	18	0	0	0	18
23	0	0	1	0	41	0	0	43
29	2	4	3	0	14	199	14	269
30	0	4	0	0	2	5	131	161
TOTALS	696	744	95	53	180	628	437	8087

PROCEDURE NEIGHBOR   CLASSIFIED BY: SOIL TYPE   DATA: NORMAL FIELD

PERCENTAGE

TO CATEGORY		O	C	M	T	S	S	C	C
TO SOIL TYPE		2	3	7	8	9	13	14	15
FROM SOIL	#								
O	2	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
C	3	0.8	87.2	2.2	0.0	0.0	1.9	4.9	0.8
SM-MS	7	0.7	0.0	90.7	0.0	0.0	0.7	2.0	2.0
S-SM	8	0.0	0.4	1.8	56.3	16.8	5.2	3.1	0.5
S	9	0.2	1.8	2.4	9.2	47.3	5.4	5.8	0.4
Ssh	13	0.6	1.2	6.5	0.0	0.0	72.6	0.6	1.8
CS	14	4.0	6.4	6.4	0.0	0.0	3.0	58.1	0.3
CSsh	15	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0
SC	16	0.4	2.8	6.7	3.2	4.3	4.2	7.4	0.4
SCsh	17	0.0	0.8	10.2	0.0	0.0	2.3	5.4	0.4
So	19	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Csh	21	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
WRk	23	0.0	0.0	0.0	0.0	0.0	0.0	0.0	2.3
Scem	29	0.0	1.9	1.5	0.0	0.0	5.6	2.2	1.1
SCcem	30	0.0	0.0	11.2	0.0	0.0	0.0	0.6	0.0

TO CATEGORY	U	U	S	C	R	S	U	TOTALS
TO SOIL TYPE	16	17	19	21	23	29	30	
FROM SOIL								
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0
3	0.3	0.3	0.0	0.0	0.3	1.1	0.3	100.0
7	0.0	0.0	0.0	0.0	0.0	0.0	4.0	100.0
8	3.8	4.0	0.9	0.0	1.7	4.8	0.5	100.0
9	5.1	7.0	1.1	0.2	2.2	8.0	3.9	100.0
13	0.0	0.6	4.2	3.0	4.2	3.6	1.2	100.0
14	1.0	4.7	0.0	5.4	0.3	5.4	5.0	100.0
15	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0
16	41.7	13.9	0.4	0.8	0.9	4.6	8.4	100.0
17	5.0	59.0	1.0	0.0	0.8	3.5	11.4	100.0
19	0.0	0.0	100.0	0.0	0.0	0.0	0.0	100.0
21	0.0	0.0	0.0	100.0	0.0	0.0	0.0	100.0
23	0.0	0.0	2.3	0.0	95.3	0.0	0.0	100.0
29	0.7	1.5	1.1	0.0	5.2	74.0	5.2	100.0
30	0.0	2.5	0.0	0.0	1.2	3.1	81.4	100.0

PROCEDURE DISCRIM CLASSIFIED BY: CATEGORY DATA: FIELD

COUNT

FROM \ TO	C	M	O	R	S	T	U	TOTALS
C	373	106	55	8	32	59	61	694
M	21	114	0	0	8	5	2	150
O	3	3	20	0	0	0	0	26
R	0	0	0	32	2	9	0	43
S	187	306	13	777	645	614	845	3387
T	74	12	0	431	389	1023	169	2098
U	179	111	8	24	138	252	977	1689
TOTALS	837	652	96	1272	1214	1962	2054	8087

PERCENTAGE

FROM \ TO	C	M	O	R	S	T	U	TOTALS
C	53.7	15.3	7.9	1.2	4.6	8.5	8.8	100.0
M	14.0	76.0	0.0	0.0	5.3	3.3	1.3	100.0
O	11.5	11.5	76.9	0.0	0.0	0.0	0.0	100.0
R	0.0	0.0	0.0	74.4	4.7	20.9	0.0	100.0
S	5.5	9.0	0.4	22.9	19.0	18.1	24.9	100.0
T	3.5	0.6	0.0	20.5	18.5	48.8	8.1	100.0
U	10.6	6.6	0.5	1.4	8.2	14.9	57.8	100.0

PROCEDURE DISCRIM CLASSIFIED BY: CATEGORY DATA: NORMAL FIELD

COUNT

FROM \ TO	C	M	O	R	S	T	U	TOTALS
C	445	52	44	8	44	13	88	694
M	25	112	0	0	6	0	7	150
O	6	0	20	0	0	0	0	26
R	0	0	0	29	9	2	3	43
S	106	266	14	695	897	872	537	3387
T	27	90	0	277	399	1197	108	2098
U	120	380	10	52	164	97	866	1689
TOTALS	729	900	88	1061	1519	2181	1609	8087

PERCENTAGE

FROM \ TO	C	M	O	R	S	T	U	TOTALS
C	64.1	7.5	6.3	1.2	6.3	1.9	12.7	100.0
M	16.7	74.7	0.0	0.0	4.0	0.0	4.7	100.0
O	23.1	0.0	76.9	0.0	0.0	0.0	0.0	100.0
R	0.0	0.0	0.0	67.4	20.9	4.7	7.0	100.0
S	3.1	7.9	0.4	20.5	26.5	25.7	15.9	100.0
T	1.3	4.3	0.0	13.2	19.0	57.1	5.1	100.0
U	7.1	22.5	0.6	3.1	9.7	5.7	51.3	100.0

PROCEDURE NEIGHBOR CLASSIFIED BY: CATEGORY DATA: FIELD

COUNT

FROM \ TO	C	M	O	R	S	T	U	TOTALS
C	586	53	12	3	1	9	30	694
M	0	150	0	0	0	0	0	150
O	0	0	26	0	0	0	0	26
R	0	0	0	43	0	0	0	43
S	349	117	8	79	1613	718	503	3387
T	162	26	1	57	187	1529	136	2098
U	146	31	2	7	130	137	1236	1689
TOTALS	1243	377	49	189	1931	2393	1905	8087

PERCENTAGE

FROM \ TO	C	M	O	R	S	T	U	TOTALS
C	84.4	7.6	1.7	0.4	0.1	1.3	4.3	100.0
M	0.0	100.0	0.0	0.0	0.0	0.0	0.0	100.0
O	0.0	0.0	100.0	0.0	0.0	0.0	0.0	100.0
R	0.0	0.0	0.0	100.0	0.0	0.0	0.0	100.0
S	10.3	3.5	0.2	2.3	47.6	21.2	14.9	100.0
T	7.7	1.2	0.0	2.7	8.9	72.9	6.5	100.0
U	8.6	1.8	0.1	0.4	7.7	8.1	73.2	100.0

PROCEDURE NEIGHBOR CLASSIFIED BY: CATEGORY DATA: NORMAL FIELD

COUNT

FROM \ TO	C	M	O	R	S	T	U	TOTALS
C	601	42	14	3	0	2	32	694
M	0	149	1	0	0	0	0	150
O	0	0	26	0	0	0	0	26
R	0	0	0	43	0	0	0	43
S	344	98	8	91	1733	772	341	3387
T	89	40	1	36	197	1663	72	2098
U	156	164	4	15	107	80	1163	1689
TOTALS	1190	493	54	188	2037	2517	1608	8087

PERCENTAGE

FROM \ TO	C	M	O	R	S	T	U	TOTALS
C	86.6	6.1	2.0	0.4	0.0	0.3	4.6	100.0
M	0.0	99.3	0.7	0.0	0.0	0.0	0.0	100.0
O	0.0	0.0	100.0	0.0	0.0	0.0	0.0	100.0
R	0.0	0.0	0.0	100.0	0.0	0.0	0.0	100.0
S	10.2	2.9	0.2	2.7	51.2	22.8	10.1	100.0
T	4.2	1.9	0.0	1.7	9.4	79.3	3.4	100.0
U	9.2	9.7	0.2	0.9	6.3	4.7	68.9	100.0

APPENDIX E
COMPUTER PROGRAM LISTINGS

APPENDIX E-1. PROGRAM FILTER

Introduction

This program implements an average-value data filter for electronic friction-cone penetrometer data, calculating the average value of q_c and f_s over a 0.5 meter depth interval, and assigning this value to the midpoint of the interval. The program is written in the SAS language. Input variables are q_c, f_s, and depth (in meters).

Listing

```
data (keep=depth q1bar f1bar);
  set datain (rename=(depth=d));
  retain                                  /* CARRY THESE VALUES FORWARD */
  q19 q18 q17 q16 q15 q14 q13 q12 q11     /* TO NEXT OBSERVATION        */
  f19 f18 f17 f16 f15 f14 f13 f12 f11;

  qcbar=mean(qc,q11,q12,q13,q14,q15,q16,q17,q18,q19); /*  CALCULATE  */
  fsbar=mean(fs,f11,f12,f13,f14,f15,f16,f17,f18,f19); /*AVERAGE VALUE*/

  depth = d-.25;  /* CALCULATE APPLICABLE DEPTH FOR AVERAGE VALUE */

  q19=q18; q18=q17; q17=q16; q16=q15; q15=q14;  /* UPDATE VALUES FOR */
        q14=q13; q13=q12; q12=q11; q11=qc;     /* NEXT OBSERVATION */
  f19=f18; f18=f17; f17=f16; f16=f15; f15=f14;
        f14=f13; f13=f12; f12=f11; f11=fs;

  if d-int(d)=0 or d-int(d)=.5 then output;/*OUTPUT VALUES EVERY 0.5 M*/

  run;
```

APPENDIX E-2. PROGRAM NORMAL

Introduction

This program implements Olsen and Malone's (36) method for normalizing electronic cone penetration test data to an effective overburden pressure of 1 tsf (96 kPa). The purpose of the program is to determine Olsen and Malone's "n" value, which is then used to calculate the normalized q_c (qcn) and the normalized friction ratio (frn). Regression analysis was used to determine the constants which describe the lines of constant "n" on the chart (which was divided into a left-hand and right-hand side), using an intrinsic function approach. The program is written in the SAS language. Input variables are qctsf (q_c in tsf), fratio (friction ratio), and sigmav (vertical effective stress in tsf).

Listing

```
data ;
set datain;

n=.;     /* INITIALIZE N TO MISSING VALUE */
logqctsf=log10(qctsf);
logsigma=log10(sigmav);

kca1=-10.47229; kca2=8.64503; kma1=1.52917; kma2=-0.61074;/*REGRESSION*/
kcb1=-3.10784; kcb2=3.78449; kmb1=0.62540; kmb2=-0.01425; /*CONSTANTS */
kcc1=-2.78006; kcc2=3.51243; kmc1=0.99220; kmc2=-0.31870;

aa=kma1*logsigma;
ba=kca1+logsigma+kma1*logfrat+kma2*logsigma-kma1*logsigma;
ca=kca2-logqctsf+kma2*logfrat-kma2*logsigma;

ab=kmb1*logsigma;
bb=kcb1+logsigma+kmb1*logfrat+kmb2*logsigma-kmb1*logsigma;
cb=kcb2-logqctsf+kmb2*logfrat-kmb2*logsigma;
```

```
ac=kmc1*logsigma;
bc=kcc1+logsigma+kmc1*logfrat+kmc2*logsigma-kmc1*logsigma;
cc=kcc2-logqctsf+kmc2*logfrat-kmc2*logsigma;

nap=(-ba+(ba*ba-4*aa*ca)**.5)/2/aa;
nam=(-ba-(ba*ba-4*aa*ca)**.5)/2/aa;
nbp=(-bb+(bb*bb-4*ab*cb)**.5)/2/ab;
nbm=(-bb-(bb*bb-4*ab*cb)**.5)/2/ab;
ncp=(-bc+(bc*bc-4*ac*cc)**.5)/2/ac;
ncm=(-bc-(bc*bc-4*ac*cc)**.5)/2/ac;

if .6<=nap<=.66 then do;
  n=nap;
  qcn=qctsf/sigmav**n;
  frn=fratio/sigmav**(1-n);
  if log10(qcn)>1.563-1.942*log10(frn) then n=.;
  end;

if .66<=nbp<=.83 then do;
  n=nbp;
  qcn=qctsf/sigmav**n;
  frn=fratio/sigmav**(1-n);
  if log10(qcn)>1.563-1.942*log10(frn) then n=.;
  end;

if .83<=ncp<=1.0 then do;
  n=ncp;
  qcn=qctsf/sigmav**n;
  frn=fratio/sigmav**(1-n);
  if log10(qcn)>1.563-1.942*log10(frn) then n=.;
  end;

if .6<=nam<=.66 then do;
  n=nam;
  qcn=qctsf/sigmav**n;
  frn=fratio/sigmav**(1-n);
  if log10(qcn)>1.563-1.942*log10(frn) then n=.;
  end;

if .66<=nbm<=.83 then do;
  n=nbm;
  qcn=qctsf/sigmav**n;
  frn=fratio/sigmav**(1-n);
  if log10(qcn)>1.563-1.942*log10(frn) then n=.;
  end;

if .83<=ncm<=1.0 then do;
  n=ncm;
  qcn=qctsf/sigmav**n;
  frn=fratio/sigmav**(1-n);
  if log10(qcn)>1.563-1.942*log10(frn) then n=.;
  end;
```

```
if n=. then do;

kca1=-16.24121; kca2=12.60360; kma1=6.84926; kma2=-2.36901;
kcb1=-7.21993; kcb2=6.64955; kmb1=12.37220; kmb2=-6.01415;
kcc1=-7.62469; kcc2=6.98551; kmc1=3.97255; kmc2=0.95756;

aa=kma1*logsigma;
ba=kca1+logsigma+kma1*logfrat+kma2*logsigma-kma1*logsigma;
ca=kca2-logqctsf+kma2*logfrat-kma2*logsigma;

ab=kmb1*logsigma;
bb=kcb1+logsigma+kmb1*logfrat+kmb2*logsigma-kmb1*logsigma;
cb=kcb2-logqctsf+kmb2*logfrat-kmb2*logsigma;

ac=kmc1*logsigma;
bc=kcc1+logsigma+kmc1*logfrat+kmc2*logsigma-kmc1*logsigma;
cc=kcc2-logqctsf+kmc2*logfrat-kmc2*logsigma;

nap=(-ba+(ba*ba-4*aa*ca)**.5)/2/aa;
nam=(-ba-(ba*ba-4*aa*ca)**.5)/2/aa;
nbp=(-bb+(bb*bb-4*ab*cb)**.5)/2/ab;
nbm=(-bb-(bb*bb-4*ab*cb)**.5)/2/ab;
ncp=(-bc+(bc*bc-4*ac*cc)**.5)/2/ac;
ncm=(-bc-(bc*bc-4*ac*cc)**.5)/2/ac;

if .6<=nap<=.66 then do;
  n=nap;
  qcn=qctsf/sigmav**n;
  frn=fratio/sigmav**(1-n);
  if log10(qcn)<1.563-1.942*log10(frn) then n=.;
  end;

if .66<=nbp<=.83 then do;
  n=nbp;
  qcn=qctsf/sigmav**n;
  frn=fratio/sigmav**(1-n);
  if log10(qcn)<1.563-1.942*log10(frn) then n=.;
  end;

if .83<=ncp<=1.0 then do;
  n=ncp;
  qcn=qctsf/sigmav**n;
  frn=fratio/sigmav**(1-n);
  if log10(qcn)<1.563-1.942*log10(frn) then n=.;
  end;

if .6<=nam<=.66 then do;
  n=nam;
  qcn=qctsf/sigmav**n;
  frn=fratio/sigmav**(1-n);
  if log10(qcn)<1.563-1.942*log10(frn) then n=.;
  end;
```

```
if .66<=nbm<=.83 then do;
  n=nbm;
  qcn=qctsf/sigmav**n;
  frn=fratio/sigmav**(1-n);
  if log10(qcn)<1.563-1.942*log10(frn) then n=.;
  end;

if .83<=ncm<=1.0 then do;
  n=ncm;
  qcn=qctsf/sigmav**n;
  frn=fratio/sigmav**(1-n);
  if log10(qcn)<1.563-1.942*log10(frn) then n=.;
  end;

end;

if n=. then do;
  qcn=qctsf;
  frn=fratio;
  end;

drop logfrat logqctsf logsigma kca1 kca2 kma1 kma2 kcb1 kcb2
     kmb1 kmb2 kcc1 kcc2 kmc1 kmc2 aa ba ca ab bb cb ac bc cc
     nap nam nbp nbm ncp ncm;

run;
```

APPENDIX E-3. PROGRAM RANDOM

Introduction

This BASIC program calculates the stationary component of a random field model, Z^{**}. The input data set, RANDOM.DAT, contains the nonnormalized residuals for the nonstationary, or trend component, from the soundings around the location to be predicted. Note that the first row of the data contains the distances (r) from the predicted sounding for input into the autocorrelation function. The autocorrelation function is assumed to be of the form rho = exp(-r/k), where k is the constant of the autocorrelation function. Missing data should be identified with a value of -99. Reference: Kulatilake and Ghosh (26).

Listing

```
10 PRINT
20 PRINT "  **********         RANDOM FIELD MODEL         **********"
30 PRINT "  **********          Z** CALCULATIONS          **********"
40 PRINT
50 PRINT "  Programmed by Kenneth J. Knox, February 1989, Univ of Florida"
60 PRINT
70 PRINT "  This program calculates the stationary component of a random field"
80 PRINT "  model, Z**.  The input data set, RANDOM.DAT, contains the "
90 PRINT "  nonnormalized residuals for the nonstationary, or trend component,"
100 PRINT "  from the soundings around the location to be predicted."
110 PRINT "  Note: the first row of data contains the distances (r) for input"
120 PRINT "  into the autocorrelation function."
130 PRINT "  Note: missing data should be recognized with a value of -99."
140 PRINT "  Ref: PENETRATION TESTING 1988 (ISOPT-1), p. 818"
150 PRINT
160 DIM VALUE(405,6), NORM(405,6), R(6), RHO(6), ZSTAR(405,6)
170 INPUT "HOW MANY OBSERVATIONS (DEPTHS) IN THE DATA?";OBS
180 INPUT "HOW MANY SOUNDINGS WITHIN THE CORRELATED REGION?";Q
190 PRINT "WHAT IS THE CONSTANT, K, FOR THE AUTOCORRELATION FUNCTION OF THE"
200 INPUT "OF THE FORM: RHO(r) = EXP(-r/K)?";K
210 INPUT "WHAT IS THE MEAN OF THE GLOBAL DATA SET?";MEAN
220 INPUT "WHAT IS THE STANDARD DEVIATION OF THE GLOBAL DATA SET?";STD
230 PRINT
240 OPEN "RANDOM.DAT" FOR INPUT AS #1
250 OPEN "RANDOM.OUT" FOR OUTPUT AS #2
260 FOR J=1 TO Q
```

```
270   INPUT #1, R(J)
280   NEXT J
290 PRINT #2, "MEAN = ";MEAN
300 PRINT #2, "STANDARD DEVIATION = ";STD
310 PRINT #2,
320 PRINT "          Z** MATRIX"
330 PRINT
340 PRINT #2, "          Z** MATRIX"
350 PRINT #2,
360 FOR I=1 TO OBS
370 PRINT
380 PRINT #2,
390   RHOSUM=0
400   FOR J=1 TO Q
410     INPUT #1, VALUE(I,J)
420     IF VALUE(I,J)=-99 THEN RHO(J)=0 ELSE RHO(J)=EXP(-R(J)/K)
430     RHOSUM=RHOSUM+RHO(J)
440     NEXT J
450    ZSUM=0
455 IF RHOSUM=0 THEN PRINT "NO OBSERVATIONS":PRINT #2,"NO OBSERVATIONS":GOTO 520
460   FOR J=1 TO Q
470     Z(J)=RHO(J)/RHOSUM*(VALUE(I,J)-MEAN)
480     ZSUM=ZSUM+Z(J)
490     NEXT J
500   PRINT "Z**(";I;") = ";ZSUM
510   PRINT #2, ZSUM
520   NEXT I
530 END
```

APPENDIX E-4. PROGRAM AUTOCOR

Introduction

This BASIC program calculates the autocorrelation coefficient for a given set of input data, in the form of (distance, value). The program assumes the data is from soundings located in a straight line, with a distance measured from a common reference. The data need not be regularly-spaced (if so, use PROGRAM AUTOCOR2), since an average distance interval and a tolerance are input parameters. Reference: Kulatilake and Ghosh (26).

Listing

```
10 REM **********************************************************
20 REM *                                                        *
30 REM *             AUTOCORRELATION COEFFICIENT                *
40 REM *                                                        *
50 REM **********************************************************
60 REM
70 REM This program calculated the autocorrelation coefficient for a given
80 REM set of input data, in the form of (distance, value).
90 REM
100 REM by Kenneth J. Knox, January 1989, Univ of Florida
110 REM
120 REM ********** INITIALIZE PROGRAM AND READ DATA **********
130 REM
140 DIM DIST(30), VALUE(30), DELTA(30,30), X(30), Y(30)
150 PRINT "              AUTOCORRELATION FUNCTION"
160 PRINT
170 PRINT "                        by Kenneth J. Knox"
180 PRINT "                           January 1989"
190 PRINT
200 READ N      : 'N=NUMBER OF OBSERVATIONS
210 FOR I=1 TO N
220    READ DIST(I), VALUE(I)
230    NEXT I
240 FOR I=1 TO N
250    FOR J=1 TO N
260       DELTA(I,J)=ABS(DIST(I)-DIST(J))
270       NEXT J
280    NEXT I
290 REM
300 REM ***** CALCULATE DELTA(DISTANCES) AND AUTOCORRELATION FUNCTION *****
```

```
310 REM
320 INPUT "INPUT DISTANCE INCREMENT, MAXIMUM DISTANCE AND TOLERANCE"; INC, DELMAX,
330 FOR DEL=0 TO DELMAX STEP INC
340 COUNT=0
350 XSUM=0
360 YSUM=0
370 SUM1=0
380 SUM2=0
390 SUM3=0
400    FOR I=1 TO N
410       FOR J=1 TO I
420          IF (((DEL-TOL)>DELTA(I,J)) OR (DELTA(I,J)>(DEL+TOL))) THEN 480
430          COUNT=COUNT+1
440          X(COUNT)=VALUE(I)
450          XSUM=XSUM+X(COUNT)
460          Y(COUNT)=VALUE(J)
470          YSUM=YSUM+Y(COUNT)
480          NEXT J
490       NEXT I
500    XBAR=XSUM/COUNT
510    YBAR=YSUM/COUNT
520    FOR I=1 TO COUNT
530       SUM1=SUM1+((X(I)-XBAR)*(Y(I)-YBAR))
540       SUM2=SUM2+(X(I)-XBAR)^2
550       SUM3=SUM3+(Y(I)-YBAR)^2
560       NEXT I
570    R=SUM1/SQR(SUM2*SUM3)
580    PRINT "FOR DISTANCE INCREMENT = ";DEL;", R = ";R
590    NEXT DEL
600 END
610 DATA ***input data***
```

APPENDIX E-5. PROGRAM AUTOCOR2

Introduction

This BASIC program calculates the autocorrelation coefficient for a given array of input data, in the form of (depth, N1, ..., Nk). The program assumes the data is from regularly-spaced soundings located in a straight line. Reference: Kulatilake and Southworth (28).

Listing

```
10 REM *********************************************************
20 REM *                                                       *
30 REM *              AUTOCORRELATION FUNCTION                 *
40 REM *                    version 2                          *
50 REM *********************************************************
60 REM
70 REM This program calculates the autocorrelation coefficient for a given
80 REM array of input data, in the form of (depth, N1, ..., Nk).
90 REM Reference: Kulatilake and Southworth, 1987
100 REM
110 REM by Kenneth J. Knox, January 1989, Univ of Florida
120 REM
130 REM ********** INITIALIZE PROGRAM AND READ DATA **********
140 REM
150 DIM DEPTH(30), VALUE(30,30), DELTA(30,30)
160 PRINT "              AUTOCORRELATION FUNCTION"
170 PRINT
180 PRINT "                        by Kenneth J. Knox"
190 PRINT "                           January 1989"
200 PRINT
210 OPEN "A:AUTOCOR.DAT" FOR INPUT AS #1
220 OPEN "A:AUTOCOR.OUT" FOR OUTPUT AS #2
230 REM ****** N = # OF DEPTHS     K = # OF SOUNDINGS ******
240 INPUT #1, N, K
250 FOR I=1 TO N
260 INPUT #1, DEPTH(I)
270 FOR J=1 TO K
280 INPUT #1, VALUE(I,J)
290    NEXT J
300    NEXT I
310 REM
320 REM ***** CALCULATE MEAN (YBAR) AND BRACKETS (DELTA) *****
330 REM
340 YSUM=0
350 COUNT=0
360 FOR I=1 TO N
```

```
370   FOR J=1 TO K
380     IF VALUE(I,J)=-99 THEN GOTO 410
390     YSUM=YSUM+VALUE(I,J)
400     COUNT=COUNT+1
410     NEXT J
420   NEXT I
430 YBAR=YSUM/COUNT
440 PRINT
450 PRINT "THE MEAN VALUE = ";YBAR
460 PRINT
470 DENOM=0
480 COUNT=0
490 FOR I=1 TO N
500   FOR J=1 TO K
510 IF VALUE(I,J)=-99 THEN GOTO 550
520     DELTA(I,J)=VALUE(I,J)-YBAR
530     DENOM=DENOM+DELTA(I,J)*DELTA(I,J)
540     COUNT=COUNT+1
550     NEXT J
560   NEXT I
570 DENOM=DENOM/COUNT
580 M=INT(.25*K+.5)
590 FOR LAG=0 TO M
600 NUM=0
610 COUNT=0
620 FOR T=1 TO K-LAG
630   FOR I=1 TO N
640     IF VALUE(I,T+LAG)=-99 THEN GOTO 680
650     IF VALUE(I,T)=-99 THEN GOTO 680
660     NUM=NUM+(VALUE(I,T+LAG)-YBAR)*(VALUE(I,T)-YBAR)
670     COUNT=COUNT+1
680     NEXT I
690   NEXT T
700 RHO=NUM/COUNT/DENOM
710 PRINT "FOR LAG INTERVAL NUMBER ";LAG;", RHO = ";RHO
720 PRINT #2, "FOR LAG INTERVAL NUMBER ";LAG;", RHO = ";RHO
730 NEXT LAG
740 END
```

APPENDIX F
STEPWISE REGRESSION SUMMARIES

<u>Choctawhatchee Bay Autocorrelation Function</u>

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable QC

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D5X1		1	0.3625	0.3625	267.8094	0.0001
2	D1		2	0.0481	0.4106	38.3863	0.0001
3	D2		3	0.0847	0.4954	78.7592	0.0001
4	D8		4	0.0504	0.5458	51.9277	0.0001
5	D3X1		5	0.0089	0.5546	9.2899	0.0024
6	X1		6	0.0055	0.5601	5.8307	0.0161
7	D1X1		7	0.0040	0.5641	4.2200	0.0405
8		D3X1	6	0.0001	0.5640	0.1026	0.7488

AUTOCORRELATION FUNCTION USED STEP 4

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable FRICTION

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D5X1		1	0.5668	0.5668	616.3491	0.0001
2	D1X1		2	0.0595	0.6263	74.8345	0.0001
3	X2		3	0.0080	0.6343	10.2275	0.0015
4	D2		4	0.0157	0.6500	21.0394	0.0001
5	D4X1		5	0.0079	0.6580	10.8216	0.0011
6		D5X1	4	0.0010	0.6570	1.3195	0.2513
7	D8		5	0.0027	0.6597	3.7088	0.0547

AUTOCORRELATION FUNCTION USED STEP 4

Choctawhatchee Bay Regression Models

Prediction of Choctawhatchee Bay Sounding E

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable QC

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D5X1		1	0.3748	0.3748	258.4299	0.0001
2	D1X1		2	0.0424	0.4173	31.3253	0.0001
3	X1		3	0.0395	0.4568	31.1920	0.0001
4	D3X1		4	0.0819	0.5387	75.9493	0.0001

LOW TERM MODEL USED STEP 3   HIGH TERM MODEL USED STEP 4

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable FRICTION

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D5X1		1	0.5734	0.5734	579.2678	0.0001
2	D1X1		2	0.0565	0.6299	65.6958	0.0001
3	D3		3	0.0068	0.6367	8.0190	0.0048
4	X2		4	0.0156	0.6523	19.2337	0.0001
5	D8		5	0.0147	0.6670	18.7848	0.0001

LOW TERM MODEL USED STEP2   HIGH TERM MODEL USED STEP 5

Prediction of Choctawhatchee Bay Sounding H

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable QC

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D5X1		1	0.4024	0.4024	290.8712	0.0001
2	D1X1		2	0.0404	0.4428	31.2589	0.0001
3	X1		3	0.0431	0.4859	36.0299	0.0001
4	D4X1		4	0.0920	0.5779	93.5176	0.0001
5	D3X2		5	0.0027	0.5806	2.7935	0.0954
6	D8		6	0.0037	0.5843	3.7843	0.0524
7	D5		7	0.0039	0.5882	4.0127	0.0458
8	D1		8	0.0097	0.5979	10.3012	0.0014
9	D3		9	0.0132	0.6112	14.4292	0.0002
10		D8	8	0.0000	0.6112	0.0000	0.9948
11		D5X1	7	0.0000	0.6112	0.0079	0.9293

LOW TERM MODEL USED STEP 4   HIGH TERM MODEL USED STEP 11

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable FRICTION

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D5X1		1	0.5772	0.5772	589.7038	0.0001
2	D1X1		2	0.0584	0.6355	69.0310	0.0001
3	X2		3	0.0075	0.6431	9.0709	0.0028
4	D4X1		4	0.0179	0.6609	22.5974	0.0001
5	D2		5	0.0104	0.6714	13.6044	0.0003
6	D8		6	0.0016	0.6730	2.0826	0.1497
7		D5X1	5	0.0002	0.6727	0.3151	0.5749
8	D1		6	0.0034	0.6761	4.4955	0.0346
9	D3X1		7	0.0017	0.6778	2.2039	0.1384

LOW TERM MODEL USED STEP 3   HIGH TERM MODEL USED STEP 9

Prediction of Choctawhatchee Bay Sounding J

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable QC

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D5X1		1	0.3289	0.3289	211.7561	0.0001
2	D1X1		2	0.0451	0.3740	31.0211	0.0001
3	X1		3	0.0447	0.4187	33.0715	0.0001
4	D3X1		4	0.0852	0.5039	73.6891	0.0001

LOW TERM MODEL USED STEP 3   HIGH TERM MODEL USED STEP 4

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable FRICTION

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D5X1		1	0.5596	0.5596	548.9139	0.0001
2	D1X1		2	0.0538	0.6134	60.0198	0.0001
3	X2		3	0.0140	0.6274	16.1180	0.0001
4	D2X1		4	0.0205	0.6479	24.9814	0.0001
5	D2		5	0.0098	0.6577	12.3111	0.0005
6	D8		6	0.0020	0.6597	2.5143	0.1136
7	D1		7	0.0024	0.6621	2.9866	0.0847
8		D2X1	6	0.0005	0.6616	0.6242	0.4299

LOW TERM MODEL USED STEP 4   HIGH TERM MODEL USED STEP 8

Prediction of Choctawhatchee Bay Sounding E Using Logs

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable QC

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D5X1		1	0.2193	0.2193	121.0802	0.0001
2	D1		2	0.0464	0.2657	27.1702	0.0001
3	D2		3	0.1528	0.4185	112.6881	0.0001
4	D6		4	0.1142	0.5327	104.5684	0.0001
5	D3		5	0.0097	0.5423	9.0055	0.0028
6		D2	4	0.0002	0.5421	0.1878	0.6650
7	D8		5	0.0111	0.5532	10.6355	0.0012

LOW TERM MODEL USED STEP 4   HIGH TERM MODEL USED STEP 7

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable FRICTION

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D4		1	0.3238	0.3238	206.3537	0.0001
2	D1		2	0.0298	0.3536	19.8299	0.0001
3	D6		3	0.0748	0.4284	56.1389	0.0001
4	D5X1		4	0.0191	0.4475	14.8302	0.0001
5	D2X1		5	0.0282	0.4757	22.9575	0.0001
6	X2		6	0.0064	0.4821	5.2516	0.0224
7	X1		7	0.0206	0.5027	17.5978	0.0001
8	D1X2		8	0.0171	0.5198	15.1418	0.0001

LOW TERM MODEL USED STEP 5   HIGH TERM MODEL USED STEP 8

Prediction of Choctawhatchee Bay Sounding H Using Logs

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable QC

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D5X1		1	0.2395	0.2395	136.0552	0.0001
2	D1		2	0.0504	0.2899	30.5833	0.0001
3	D2		3	0.1615	0.4514	126.5741	0.0001
4	D7		4	0.1066	0.5580	103.5155	0.0001
5	D5X2		5	0.0113	0.5693	11.1956	0.0009
6	X2		6	0.0037	0.5730	3.7454	0.0536
7	D1X1		7	0.0145	0.5876	15.0234	0.0001
8	D4X2		8	0.0119	0.5995	12.6765	0.0004
9	D8		9	0.0034	0.6029	3.5900	0.0588
10	D3		10	0.0365	0.6394	42.7874	0.0001
11	D6		11	0.0067	0.6460	7.9440	0.0051
12	D1X2		12	0.0032	0.6493	3.8714	0.0498
13		D4X2	11	0.0013	0.6480	1.5126	0.2194
14	X1		12	0.0029	0.6509	3.4962	0.0622
15		X2	11	0.0009	0.6500	1.1163	0.2913
16	D4X1		12	0.0040	0.6540	4.8876	0.0276
17		D5X1	11	0.0001	0.6539	0.1164	0.7332
18	D2X1		12	0.0019	0.6558	2.3032	0.1299

LOW TERM MODEL USED STEP 5   HIGH TERM MODEL USED STEP 18

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable FRICTION

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D4		1	0.3067	0.3067	191.1109	0.0001
2	D1		2	0.0487	0.3554	32.5749	0.0001
3	D6		3	0.0782	0.4336	59.3885	0.0001
4	D5X1		4	0.0200	0.4537	15.7430	0.0001
5	D1X1		5	0.0235	0.4772	19.2544	0.0001
6	X2		6	0.0193	0.4965	16.3846	0.0001
7	X1		7	0.0215	0.5180	18.9709	0.0001
8	D5X2		8	0.0177	0.5357	16.2292	0.0001

LOW TERM MODEL USED STEP 5   HIGH TERM MODEL USED STEP 8

Prediction of Choctawhatchee Bay Sounding J Using Logs

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable QC

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D5X1		1	0.1927	0.1927	103.1417	0.0001
2	D1		2	0.0547	0.2474	31.3301	0.0001
3	D2		3	0.1662	0.4136	121.8562	0.0001
4	D6		4	0.0940	0.5076	81.8502	0.0001
5	D5X2		5	0.0070	0.5146	6.1954	0.0132
6	D3		6	0.0061	0.5207	5.4370	0.0202
7		D2	5	0.0000	0.5207	0.0012	0.9721
8	D8		6	0.0130	0.5337	11.9471	0.0006

LOW TERM MODEL USED STEP 4   HIGH TERM MODEL USED STEP 8

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable FRICTION

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D4		1	0.2895	0.2895	176.0447	0.0001
2	D1		2	0.0479	0.3374	31.1321	0.0001
3	D5		3	0.0767	0.4140	56.2523	0.0001
4	D5X1		4	0.0224	0.4365	17.0867	0.0001
5	D2X1		5	0.0127	0.4492	9.8886	0.0018
6	X2		6	0.0177	0.4669	14.1851	0.0002
7	X1		7	0.0317	0.4987	26.9771	0.0001
8	D5X2		8	0.0174	0.5161	15.3005	0.0001
9	D3X1		9	0.0031	0.5192	2.7574	0.0975
10		D5X1	8	0.0002	0.5190	0.1478	0.7009

LOW TERM MODEL USED STEP 6   HIGH TERM MODEL USED STEP 10

Apalachicola River Regression Models

Prediction of Apalachicola River Sounding #11

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable N

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D1		1	0.1412	0.1412	36.0128	0.0001
2	D5X1		2	0.1904	0.3316	62.0849	0.0001
3	D7		3	0.0129	0.3445	4.2833	0.0397
4	D2X2		4	0.0236	0.3682	8.0811	0.0049
5		D5X1	3	0.0004	0.3678	0.1246	0.7244

LOW TERM MODEL USED STEP 2 HIGH TERM MODEL USED STEP 5

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable LOGN

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D1		1	0.4459	0.4459	176.2034	0.0001
2	D4		2	0.2103	0.6561	133.2883	0.0001
3	D1X2		3	0.0588	0.7149	44.7632	0.0001
4	D1X1		4	0.0067	0.7216	5.1595	0.0241
5	D8		5	0.0036	0.7252	2.8477	0.0930
6	D2		6	0.0164	0.7416	13.5530	0.0003

LOW TERM MODEL USED STEP 3 HIGH TERM MODEL USED STEP 6

Prediction of Apalachicola River Sounding #16

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable N

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D1		1	0.1341	0.1341	33.7521	0.0001
2	D4X1		2	0.2016	0.3356	65.8374	0.0001
3	D6		3	0.0171	0.3528	5.7115	0.0177
4	D5X1		4	0.0146	0.3673	4.9589	0.0270
5	D2		5	0.0097	0.3770	3.3171	0.0700
6		D1	4	0.0010	0.3760	0.3590	0.5497
7	D3X1		5	0.0073	0.3833	2.5360	0.1128

LOW TERM MODEL USED STEP 2 HIGH TERM MODEL USED STEP 7

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable LOGN

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D1		1	0.4356	0.4356	168.2783	0.0001
2	D3		2	0.2100	0.6456	128.5691	0.0001
3	D1X2		3	0.0652	0.7108	48.6813	0.0001

LOW TERM MODEL USED STEP 2 HIGH TERM MODEL USED STEP 3

Prediction of Apalachicola River Sounding #19

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable N

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D1		1	0.1577	0.1577	39.6825	0.0001
2	D5X1		2	0.1813	0.3390	57.8650	0.0001
3	D7		3	0.0211	0.3601	6.9326	0.0091
4	D2X2		4	0.0302	0.3902	10.3381	0.0015
5		D5X1	3	0.0025	0.3877	0.8646	0.3535

LOW TERM MODEL USED STEP 2   HIGH TERM MODEL USED STEP 5

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable LOGN

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D1		1	0.4671	0.4671	185.8142	0.0001
2	D4		2	0.2181	0.6852	146.2275	0.0001
3	D1X2		3	0.0602	0.7454	49.6291	0.0001
4	D1X1		4	0.0065	0.7519	5.4656	0.0203
5	D5X2		5	0.0030	0.7548	2.5087	0.1147
6	D4X1		6	0.0158	0.7707	14.3026	0.0002

LOW TERM MODEL USED STEP 3   HIGH TERM MODEL USED STEP 6

Archer Landfill Regression Models

Prediction of Archer Landfill Sounding #4

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable LOGQC

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D1		1	0.7090	0.7090	426.4126	0.0001
2	Y2		2	0.0662	0.7752	51.2417	0.0001
3	D3		3	0.0389	0.8141	36.1663	0.0001
4	D1X1		4	0.0077	0.8218	7.4135	0.0071
5	D5X2		5	0.0217	0.8435	23.7309	0.0001
6	X1		6	0.0080	0.8515	9.1323	0.0029
7	X2		7	0.0117	0.8631	14.4218	0.0002
8	D1Y2		8	0.0027	0.8659	3.4294	0.0658
9		Y2	7	0.0001	0.8658	0.0902	0.7643
10	D1X2		8	0.0048	0.8706	6.1890	0.0138
11	Y1		9	0.0063	0.8769	8.5186	0.0040

LOW TERM MODEL USED STEP 3 HIGH TERM MODEL USED STEP 11

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable LOGFS

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D1		1	0.6593	0.6593	338.6691	0.0001
2	Y2		2	0.1278	0.7871	104.4271	0.0001
3	D1Y1		3	0.0217	0.8088	19.6082	0.0001
4	D2Y1		4	0.0402	0.8489	45.7290	0.0001
5	D5X1		5	0.0055	0.8545	6.4980	0.0117
6	D2X1		6	0.0087	0.8632	10.8155	0.0012
7	D5		7	0.0057	0.8688	7.2993	0.0076
8		D2Y1	6	0.0013	0.8676	1.6311	0.2033
9	X1		7	0.0043	0.8719	5.6529	0.0185
10	D1X1		8	0.0047	0.8766	6.4321	0.0121
11		D1Y1	7	0.0011	0.8755	1.4779	0.2258
12	D7		8	0.0069	0.8824	9.8546	0.0020
13		D2X1	7	0.0009	0.8815	1.2646	0.2624
14	Y1		8	0.0038	0.8853	5.5860	0.0192
15	X2		9	0.0034	0.8887	5.0873	0.0254
16	D1X2		10	0.0033	0.8920	5.0223	0.0263

17	D1Y1		11	0.0031	0.8951	4.8658	0.0288
18	D5X2		12	0.0017	0.8968	2.7073	0.1018
19	D5Y1		13	0.0061	0.9029	10.2075	0.0017
20	D4X1		14	0.0017	0.9045	2.8618	0.0926

LOW TERM MODEL USED STEP 4   HIGH TERM MODEL USED STEP 20

Prediction of Archer Landfill Sounding #5

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable LOGQC

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D1		1	0.6682	0.6682	352.5056	0.0001
2	Y2		2	0.0984	0.7667	73.3880	0.0001
3	D3		3	0.0420	0.8086	37.9512	0.0001
4	D1X2		4	0.0119	0.8205	11.3642	0.0009
5	D5X2		5	0.0180	0.8386	19.1177	0.0001
6	X1		6	0.0115	0.8501	13.0581	0.0004
7	Y1		7	0.0086	0.8587	10.3072	0.0016
8	X2		8	0.0036	0.8623	4.3704	0.0381
9	D2		9	0.0032	0.8654	3.9352	0.0489
10	D6		10	0.0122	0.8777	16.5758	0.0001
11		D1	9	0.0001	0.8776	0.1446	0.7042

LOW TERM MODEL USED STEP 5   HIGH TERM MODEL USED STEP 11

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable LOGFS

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D1		1	0.6647	0.6647	346.9552	0.0001
2	Y2		2	0.1198	0.7845	96.7581	0.0001
3	D3		3	0.0247	0.8092	22.4109	0.0001
4	D1Y1		4	0.0162	0.8254	15.9484	0.0001
5	D3Y1		5	0.0195	0.8449	21.4480	0.0001
6	D8		6	0.0035	0.8484	3.9813	0.0476
7		D3	5	0.0000	0.8484	0.0143	0.9050
8	D2Y1		6	0.0032	0.8516	3.6438	0.0580
9		D1Y1	5	0.0017	0.8499	1.9987	0.1593
10	D5Y2		6	0.0053	0.8552	6.2600	0.0133
11	D1X2		7	0.0023	0.8575	2.7837	0.0971

12	X1		8	0.0086	0.8662	10.8243	0.0012
13		D5Y2	7	0.0017	0.8645	2.0737	0.1517
14	X2		8	0.0055	0.8701	7.1718	0.0081
15	D7		9	0.0031	0.8732	4.1056	0.0443
16	D4X2		10	0.0107	0.8838	15.2366	0.0001
17		D3Y1	9	0.0007	0.8831	1.0242	0.3130
18		D2Y1	8	0.0004	0.8828	0.5053	0.4782
19		X2	7	0.0007	0.8820	1.0423	0.3088
20	Y1		8	0.0038	0.8858	5.5960	0.0191

LOW TERM MODEL USED STEP 5   HIGH TERM MODEL USED STEP 20

Prediction of Archer Landfill Sounding #8

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable LOGQC

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D1		1	0.6739	0.6739	363.7762	0.0001
2	Y2		2	0.0852	0.7591	61.8734	0.0001
3	D3		3	0.0454	0.8045	40.3662	0.0001
4	D1X1		4	0.0101	0.8146	9.4490	0.0025
5	D5X2		5	0.0174	0.8320	17.8703	0.0001
6	X1		6	0.0069	0.8390	7.3546	0.0074
7	D2		7	0.0035	0.8425	3.7748	0.0537
8	D7		8	0.0068	0.8492	7.5744	0.0066
9		D1	7	0.0008	0.8484	0.9171	0.3396
10	X2		8	0.0034	0.8518	3.9062	0.0497
11	Y1		9	0.0030	0.8548	3.4672	0.0643

LOW TERM MODEL USED STEP 5   HIGH TERM MODEL USED STEP 11

All variables in the model are significant at the 0.1500 level.
No other variable met the 0.1500 significance level for entry into the model.

Summary of Stepwise Procedure for Dependent Variable LOGFS

Step	Variable Entered	Variable Removed	Number In	Partial R**2	Model R**2	F	Prob>F
1	D1		1	0.6653	0.6653	349.8589	0.0001
2	Y2		2	0.1175	0.7828	94.6212	0.0001
3	D3		3	0.0259	0.8086	23.5154	0.0001
4	D1Y1		4	0.0158	0.8244	15.5658	0.0001
5	D3Y1		5	0.0173	0.8418	18.8486	0.0001
6		D3	4	0.0019	0.8399	2.0656	0.1525
7	D8		5	0.0045	0.8444	4.9571	0.0273
8	D2Y2		6	0.0023	0.8466	2.5600	0.1114

LOW TERM MODEL USED STEP 4   HIGH TERM MODEL USED STEP 8

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BIOGRAPHICAL SKETCH

Kenneth James Knox [redacted] The first of two children of [redacted] at the age of four Ken moved to Tampa, where he remained through his high school years. Upon graduation from H.B. Plant High in Tampa, Ken accepted a four-year Air Force ROTC scholarship to attend the Georgia Institute of Technology in Atlanta, Georgia.

While at Georgia Tech, Ken participated in the Cooperative Program, working with Greiner Engineering of Tampa. While still attending Georgia Tech, Ken married his childhood sweetheart, [redacted] He graduated with highest honors in June, 1978, with a Bachelor of Civil Engineering degree, and a commission as a second lieutenant in the United States Air Force.

Ken entered active duty in August, 1978, at the Air Force Engineering and Services Center, Tyndall Air Force Base, Panama City, Florida. As a Geotechnical Research Engineer in the Rapid Runway Repair Branch, Ken monitored research contracts and conducted in-house research on the expedient repair of bomb-damaged runways. He published two magazine articles and three Air Force technical reports while at Tyndall.

In September, 1980, the Air Force sponsored Ken to attend graduate school. He attended Stanford University in Stanford, California, receiving a Master of Science degree in civil engineering in June 1981.

Upon his graduation from Stanford, the Air Force sent Ken and his family overseas to Headquarters, United States Air Forces in Europe (USAFE), Ramstein Air Base, West Germany. He worked for the Deputy Chief of Staff for Engineering and Services as a staff civil engineer. Ken's responsibilities included development of master plans, and the management of design and construction contracts for airbase facilities in Germany, Turkey, Egypt, and Oman.

Following his three-year tour of duty in Germany, the Air Force sent Ken to the U.S. Air Force Academy in Colorado Springs, Colorado, where he became a civil engineering instructor. Ken spent two years at the Academy, teaching statics and dynamics, fluid mechanics, and environmental engineering, and directing a review course for the Engineer-in-Training examination. While in Colorado, [redacted] blessed with a fine son [redacted]

Ken was fortunate enough to be selected to pursue his doctorate under sponsorship of the Academy. He elected to return to his home state of Florida and the University of Florida for his doctoral studies in August, 1986.

Following a very rewarding three years of study, Ken will receive his Ph.D. degree in August, 1989. Not the least of Ken and Pat's accomplishments while in Gainesville was the expansion of their family with the birth of a beautiful little girl, [redacted] Ken and his family will be returning to Colorado Springs and the Air Force Academy in the summer of 1989, where he will resume his teaching duties.

Ken is a registered professional engineer in Florida. He is a member of the American Society of Civil Engineers, the Society of American Military Engineers, the Air Force Association, The Retired

Officers Association, and Tau Beta Pi. His military decorations include the Meritorious Service Medal with one oak leaf cluster and the Air Force Commendation Medal.

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Frank C. Townsend, Chair
Professor of Civil Engineering

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

John L. Davidson
Professor of Civil Engineering

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Michael C. McVay
Associate Professor of Civil Engineering

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

David Bloomquist
Associate Engineer

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Joseph N. Wilson

Joseph N. Wilson
Assistant Professor of Computer and Information Sciences

This dissertation was submitted to the Graduate Faculty of the College of Engineering and to the Graduate School and was accepted as partial fulfillment of the requirements for the degree of Doctor of Philosophy.

August 1989

Dean, College of Engineering

Dean, Graduate School